MINISTERUL EDUCAȚIEI ȘI CERCETĂRII

UNIVERSITATEA NAȚIONALĂ DE ȘTIINȚĂ ȘI TEHNOLOGIE POLITEHNICA BUCUREŞTI

ȘCOALA DOCTORALĂ INGINERIE ENERGETICĂ

Summary

Monitoring and Control of Power Systems Using Artificial Intelligence Techniques

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București
July 2025

REZUMAT

Cercetarea doctorală propusă se concentrează pe dezvoltarea și aplicarea unor metode avansate bazate pe inteligență artificială în domeniul energetic, cu accent pe optimizarea funcționării rețelelor electrice, prognoza consumului de energie și integrarea surselor regenerabile. În prima parte a tezei sunt analizate fundamentele teoretice ale algoritmilor de inteligență artificială – rețele neuronale artificiale, metode de clusterizare, algoritmi evolutivi și logica fuzzy – și este evaluat stadiul actual al aplicațiilor acestora în sectorul electroenergetic. Pe această bază, sunt dezvoltate modele performante de prognoză a consumului de energie electrică folosind rețele neuronale de tip convoluțional, capabile să încorporeze variații sezoniere și anomalii, precum cele apărute în perioada pandemiei COVID-19 sau influența prosumatorilor. Rezultatele obținute sunt validate prin indicatori statistici relevanți și sunt comparate cu rezultatele oficiale ale Transelectrica, evidențiind superioritatea abordărilor bazate pe deep learning.

În cea de-a doua parte a lucrării sunt investigate metode de optimizare evolutivă pentru probleme critice ale sistemelor electroenergetice. Sunt propuse și analizate îmbunătățiri ale algoritmului Salpului Marin. Aplicațiile practice se axează pe repartizarea optimă a puterii reactive și alocarea capacității de racordare a surselor regenerabile, ambele esențiale pentru funcționarea sigură și eficientă a rețelelor moderne.

SUMMARY

The proposed doctoral research focuses on the development and application of advanced methods based on artificial intelligence in the energy sector, with an emphasis on optimizing the operation of power grids, forecasting energy consumption, and integrating renewable energy sources. The first part of the thesis analyses the theoretical foundations of artificial intelligence algorithms—artificial neural networks, clustering methods, evolutionary algorithms, and fuzzy logic—and evaluates the current state of their applications in the power systems sector.

Building on this foundation, high-performance models for forecasting electricity consumption are developed using convolutional neural networks, capable of incorporating seasonal variations and anomalies such as those arising during the COVID-19 pandemic or the influence of prosumers. The results are validated through relevant statistical indicators and compared with official data provided by Transelectrica, highlighting the superiority of deep learning-based approaches.

The second part of the thesis investigates evolutionary optimization methods for addressing critical problems in power systems. Improvements to the Salp Swarm Algorithm are proposed and analyzed. Practical applications focus on the optimal allocation of reactive power and the assignment of grid connection capacity for renewable energy sources—both essential for the safe and efficient operation of modern power networks.

1.INTRODUCERE

Motivația studiului

Artificial intelligence is one of the main drivers of digitization and process efficiency in many domains, having a significant impact on modern society. Some of the most relevant applications in daily life include image processing, automatic speech-to-text conversion, autonomous vehicle driving, and targeted advertising for customers [1]. With the technological advances in the field of artificial intelligence (e.g., the development of high-performance algorithms and the increase in the processing power of hardware components), the integration of these techniques in the monitoring, operation and control of electrical energy systems has become a priority for a large part of the academic community, aiming to achieve the transition to the digital era.

The importance of the subject is also reflected in the number of articles and books published over time. As can be seen in the figure below, the last few years have seen an increase in the number of publications involving applications of artificial intelligence in the field of power systems. In 2024, the number of publications indexed in the Google Scholar platform in this field exceeded the threshold of 30,000.

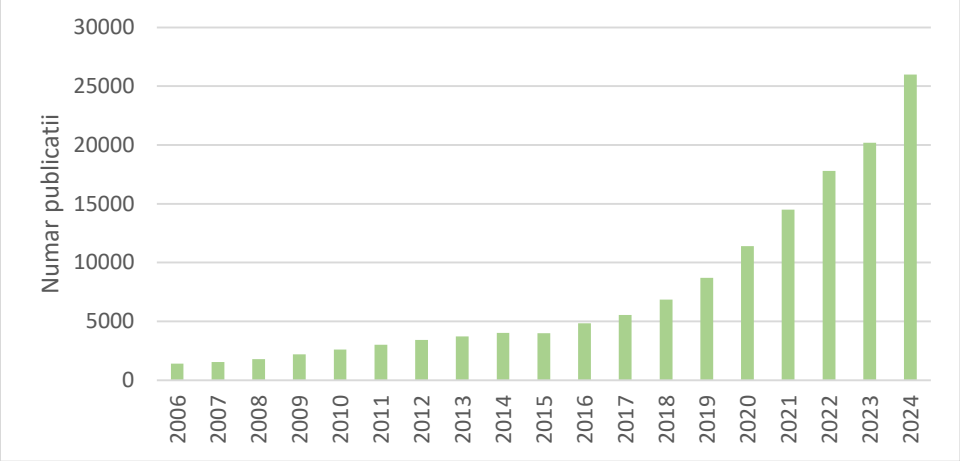


Fig. 1.1 Numărul publicațiilor indexate în baza de date Google Scholar în perioada 2006−2024 folosind cuvinte cheie: “artificial intelligence” și “power systems”

In the current context, in which it is desired and imposed to generate as much energy as possible from renewable sources, in order to reduce greenhouse gas emissions, the monitoring and control of electricity systems is becoming an increasingly difficult task. The difficulty of expanding the infrastructure of the electricity grids for economic, technical and environmental reasons leads to the need to operate modern electricity systems close to their capacity. To ensure reliability and safety in operation, the application of methods to optimize operation is vital. Thus, intelligent control of the devices within an electricity system is required in order to achieve various technical or economic objectives. The large number of equipment and consumption points make these tasks difficult, but with the help of new technologies such as

Big Data and IoT (*Internet of Things*) these challenges can be solved by using intelligent algorithms for monitoring, diagnosis and control. [2]

Scopul studiului

The main *objectives of the doctoral thesis* are to identify solutions for three important problems in the operation of electricity systems, namely the forecasting of electricity consumption, the optimization of the operation of the electricity grid through the optimal distribution of the reactive power and the optimal allocation of the available capacity in the electricity grid. In this regard, the possibility of applying AI-based techniques in solving these problems is being investigated.

The need for modern and high-performance forecasting algorithms is essential, in the context in which consumption characteristics change and thus current methodologies become non-performing and difficult to adapt. A recent consequence of the change in the consumption curve at the level of the national system is the massive integration of prosumers, whose energy produced is not quantified and aggregated at the level of the dispatcher, so that during sunny days consumption decreases significantly.

Due to the high interest from investors to deploy a large number of renewables-based plants, the current electricity grid cannot integrate all demands, resulting in high costs of strengthening and upgrading the grid to be able to meet demand. In this regard, ANRE has amended the connection regulation and stipulates the need for a methodology for allocating the capacity of the electricity grid. In this regard, the doctoral thesis proposes a method based on AI algorithms to maximize the power that can be installed in the network [3].

Structure of the doctoral thesis

The doctoral thesis is structured on six chapters. The first Chapter presents the current state of research on the application of artificial intelligence algorithms in the energy field, proving the usefulness and interest in solving the various problems that arise in the design and operation of power systems using AI techniques. The chapter presents a bibliographic study for the application of various algorithms, such as artificial neural networks, clustering technique, metaheuristic algorithms or fuzzy logic.

The second chapter details how artificial neural networks work. Given the wide applicability of these algorithms, as well as the complexity of the problems in the energy field, several variations of neural networks are presented: multilayer perceptron, recurrent neural networks and convolution neural networks. Also, methods to improve accuracy through various techniques to prevent the phenomenon of overdrive are also exposed.

Chapter 3 addresses the issue of electricity consumption forecasting, highlighting in the first part the factors influencing energy consumption. A method of forecasting for the next day of consumption at the level of the national energy system, based on neural networks, is presented. Comparing the results with those of a multilinear regression and the official results of Transelectrica, the superiority of neural networks is demonstrated. The analysis was carried out in two periods that produced major changes in the energy system, namely the COVID-19 pandemic in which the consumption pattern was changed due to the restrictions on carrying out numerous activities, as well as in 2025, in which prosumers began to play a strong role in

domestic production. It is thus highlighted that various socio-economic phenomena must be taken into account in the preparation of forecasts and the models must be periodically adapted to the latest requirements.

Chapter 3 presents a series of evolutionary calculation algorithms, such as the genetic algorithm, the lion ant algorithm or the salp algorithm. Improvements to the operating mechanisms for the latter are also proposed and the performance of the standard and improved versions is evaluated using reference functions in the field of optimizations.

One of the most important optimization problems in power systems is the optimal distribution of reactive power, with the aim of maintaining the voltage level in the permissible bands and reducing power losses. The formulation of the problem is presented in the 5th Chapter, where the performance of the improved salp optimization algorithm on two test networks is evaluated.

Chapter 6, "*Optimal allocation of available capacity to connect energy sources to electricity grids*" addresses an important issue regarding the transition of the energy sector to renewable sources. Due to the high costs of modernization and expansion of electricity grids, in order to increase the degree of integration of renewable energy sources, it is necessary that the electricity grid is operated as close as possible to the operating limits. In this regard, an optimization algorithm is proposed for the optimal allocation of the capacity of new generation sources in an electricity grid.

2.STATE OF THE ART OF ARTIFICIAL INTELLIGENCE APPLICATIONS IN THE ENERGY FIELD

2.1. Neural Networks

The technological advances made over the last decade in the field of artificial intelligence, especially in the area of neural networks, create the possibility that these techniques can be used in a wide range of fields, obtaining very good results. The current state of research in the area of neural networks is due to several factors, including:

Creating highly engaged communities focused on the study of neural networks, on different platforms (e.g. GitHub, StackOverflow);

The emergence of specialized software programs (e.g. Scikit-Learn, Tensorflow, PyTorch, Matlab, etc.) that allow the implementation of complex architectures;

The emergence of high-performance hardware components, such as graphics processing units (GPUs) that allow a high computational effort, thus reducing the time required to train neural networks.

Artificial neural networks are generally used to solve problems with supervised learning, which involve determining a function that can correspond the input and output values of a process, based on a set of input-output examples. Fig. 2.1 illustrates the main steps taken in determining a supervised learning model:Dividing the initial set of input-output pairs into two subsets, one for training and one for testing;

Training the model, assuming the determination of the correspondence function between the input values and the output values based on the examples in the training set;

Applying the obtained model to the input values of the examples in the test set;

Comparison of the results obtained by the model with the correct output values and evaluation of errors;

Change the parameters of the model and retrain it, until the error value is satisfactory.

Supervised learning involves two categories of problems that can be solved:

Classification problems, where the purpose of the model is to identify the representative class of an example in a predefined set of classes. A current challenge in the field of artificial intelligence is image processing, neural networks being used for the purpose of recognizing different elements in images;

Regression problems, in which the model produces, based on inputs, one or more real values, representing an estimate of the output of a process. The forecast of energy consumption is part of this class of problems, the outputs of the neural network representing the values forecasted over the time intervals considered.

The flexibility and diversity of neural network architectures leads to the need to study several typologies, in order to choose the best one to solve the problem considered. Next, the main types of neural networks used in solving classification and regression problems will be presented.

Exemplu	Mărimi intrare	Mărimi ieșire
1	$[x_{1,1}, x_{2,1}, \dots, x_{n,1}]$	$[y_{1,1}, y_{2,1}, \dots, y_{a,1}]$
2	$[x_{1,2}, x_{2,2}, \dots, x_{n,2}]$	$[y_{1,2}, y_{2,2}, \dots, y_{a,2}]$
⋮	⋮	⋮
n	$[x_{1,m}, x_{2,m}, \dots, x_{n,m}]$	$[y_{1,b}, y_{2,b}, \dots, y_{a,b}]$

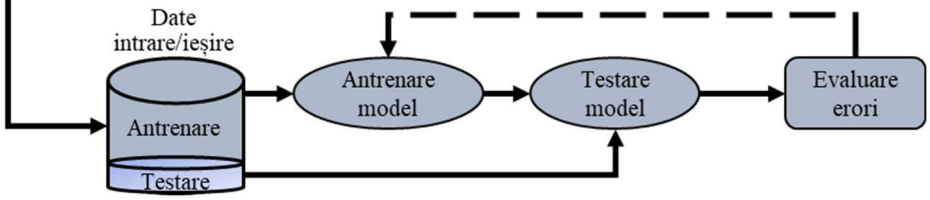


Fig. 2.1 Schemativ of a general supervised learning algorithm

2.1.1. Applications of neural networks in monitoring and controlling power systems

The number of applications of neural networks in the energy sector has seen a significant increase in the last two decades, given the success of these techniques in a wide variety of fields of activity (image processing, marketing, transport, etc.). Next, the main uses of artificial neural networks in monitoring and controlling electrical energy systems will be briefly presented.

Forecasting of electricity consumption and production

A major interest given to the subject of forecasting in the field of energy can be seen from the number of publications in the specialized literature. Fig. 2.2 shows the evolution of the number of articles and books indexed in the Google Scholar platform, segregating the main objectives to be forecasted: consumption, generation from photovoltaic sources, generation from wind sources, energy price [4]. There has been a sharp increase in the number of publications over the years, with a doubling of the annual number of publications in 2024 compared to 2020. The greatest interest is the problem of forecasting electricity consumption, which accounts for about 70% of the total number of publications found in this category. This is due to the large number of variations of the problem, with multiple time horizons for which the forecast can be made (very short, short, medium or long term) and the level of aggregation (individual, zonal or national consumption).

Numerous articles address neural networks as a method of solving forecasting problems in power systems. Of these, a good part deals with the forecasting of electricity consumption at the system level [5], [6], while studies in recent years have also focused on low aggregation levels, up to the building level [7], [8]. Also, the literature presents numerous studies on the forecasting of production from wind or photovoltaic sources [9], [10]. In general, production

forecasts are made for short periods of time, due to the stochastic nature of meteorological factors (e.g. wind speed and direction, cloudiness, solar irradiation, etc.).

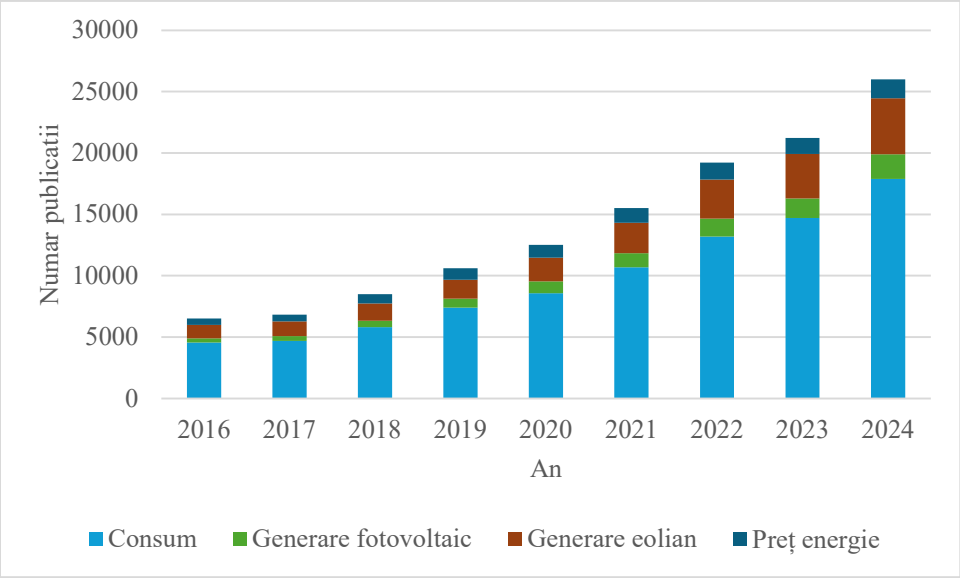


Fig. 2.2 Evolution of the number of publications indexed in the Google Scholar platform using the keywords: "load forecasting", "solar power forecasting", "wind power forecasting", "electricity price forecasting"

Considering the high degree of uncertainty associated with electrical loads, caused by a wide range of factors (i.e., meteorological, economic and social), a large amount of data and advanced calculation methods are necessary to obtain a satisfactory accuracy of the short-term consumption forecast. In this regard, numerous methods have been proposed over the years to solve this complex problem. Classical methods are based on statistical models, time series analysis, including ARIMA (Autoregressive Integrated Moving Average) [11] and variations of this method: ARIMA with exogenous variables (ARIMAX) and ARIMA with periodic components (SARIMA) [12]. In order to better adapt to the ever-changing nature of consumption, numerous studies apply modern calculation techniques, such as genetic algorithms [13] or fuzzy logic [14]. Models based on machine learning have captured the attention of the academic community, proving to have a high efficiency in solving complex problems, allowing the creation of high-performance models, which can incorporate and model the nonlinear dependencies between consumption and different external factors. Commonly used methods include support vector regression machines [15] and multilayer perceptron artificial neural networks [16].

Neural networks are an effective method to solve the problem of energy consumption, given their ability to learn and extract relevant information only from the data presented, without requiring its processing. Numerous types of neural networks have been used in the literature, each with its own advantages. Bouktif and. al. [5] studied the performance of recurrent neural networks, LSTM and GRU, for the forecasting of electricity consumption at the level of the French electricity system. Several architectures were studied in the study, with the best achieving an average error of 200 MW. In paper [17], the authors proposed a set of convolution neural networks for forecasting New York City's electricity consumption for the next day. The training of the neural networks was performed in parallel, subsequently an average of the

results offered by each neural network individually, this technique being called bootstrap aggregation, reaching a relative average error of 33%. In [18], the authors propose an architecture involving a dilation convolution neural network, which highlights the relationship between values at the same time recorded on different days. The case study involves the next-day forecast of the state of Texas, obtaining a relative mean error of 2.7%. The paper [19] presents a methodology based on MLP neural networks for forecasting the power produced by wind power plants. The methodology involves using clustering techniques, to group similar time periods and build different models for each cluster. Table 2.1 presents a summary analysis of the literature in the field of forecasting electricity consumption and production.

Tabelul 2.1 Taxonomy on forecasting algorithms in the energy filed

Reference	**Forecast type**	**Time horizon**	**Level of aggregation**	**Method**
Bouktif *et. al.* [5]	Consumption	Medium term	National (France)	LSTM / GRU
Tang *et. al.* [20]	Consumption	Short term	National (Slovakia)	RNR bidirectional
Dorado Rueda *et. al.* [6]	Consumption	Short term	National (France)	CNN
Nichiforov *et. al.* [7]	Consumption	Short term	Building	MLP autoreggresive
Dagdougui *et. al.* [8]	Consumption	Short term	Building	MLP
Dong *et. al.* [17]	Consumption	Short term	City	CNN
Shen *et. al.* [18]	Consumption	Short term	Regional (Texas)	CNN
Hernández *et. al.* [16]	Consumption	Short term	Microgrid	MLP
Nichiforov *et. al.* [21]	Consumption	Short term	City	MLP autoreggresive
Pramono *et. al.* [22]	Consumption	Short term	National (Switzerland+ New England)	CNN-LSTM
Agrawal *et. al.* [23]	Consumption	Long term	Regional (New England)	LSTM
Sangrody *et. al.* [24]	Consumption	Long term	Regional (New England)	MLP + RNR
Sadaei *et. al.* [25]	Consumption	Short term	City	CNN + fuzzy

Han *et. al.* [26]	Consumption	Short+medium term	City	CNN / LSTM
Liu *et. al.* [9]	Wind Energy	Very short term	−	LSTM
Wu *et. al.* [19]	Wind Energy	Short term	−	MLP + clusterizare
Gensler *et. al.* [27]	Solar Energy	Short term	−	LSTM + autoencoder
Lin *et. al.* [10]	Solar Energy	Short term	−	Temporal CNN
Wang *et. al.* [28]	Solar Energy	Short term	−	LSTM+gaussian reggresion

Static state estimation

The state of an electrical power system involves determining all the state quantities attached to the nodes and its sides:

injections of active and reactive power into network nodes;
the moduli and arguments of the voltages in each node of the network;
active and reactive power circulations through the sides of the network.

Static state estimation is an indispensable process for the operation of power systems in real time, assuming the determination of state quantities with sufficiently good accuracy, based on a limited amount of information. The data used by a health estimator can come from various sources:

measurements of state variables;
processing the mathematical model of the system;
- information known without measurements being made, called pseudo-measurements (e.g. the value of the voltage at the generating nodes) [29].

The classical methods of calculating the steady state require the knowledge of a fixed number of quantities and variables in order to converge to the solution. These calculation methods cannot be applied in real time, there are several difficulties in real power systems:

errors of measuring devices and means of telecommunication;
the absence of measuring devices in certain nodes of the system;
delay of measurements;
errors in network parameters.

In order to solve these sources of errors, the status estimators must contain high-performance procedures for filtering and detecting erroneous data [30]. In recent years, solutions based on neural networks for state estimation have been proposed in the literature. Miranda et. al. [31] proposed the use of an autoencoder neural network, whose general architecture is presented in Fig. 2.3. This type of neural network reconstructs the input received at the output, with the aim of filtering out any erroneous data received at the input. To solve the problem of static state estimation, the autoencoder receives all the modules and arguments of the nodal voltages as input, and in order to simulate possible measurement errors, some values are altered, the neural network being able to reconstruct the real values with 99% accuracy. Given the increase in the

number of cyberattacks in the recent period [32], the paper [33] proposed an autoregressive neural network to identify false data injected into state estimators. The development of the smart grid concept has led to an increase in interest in the application of specific techniques to transmission networks and in the distribution sector, including the problem of state estimation [34], [35].

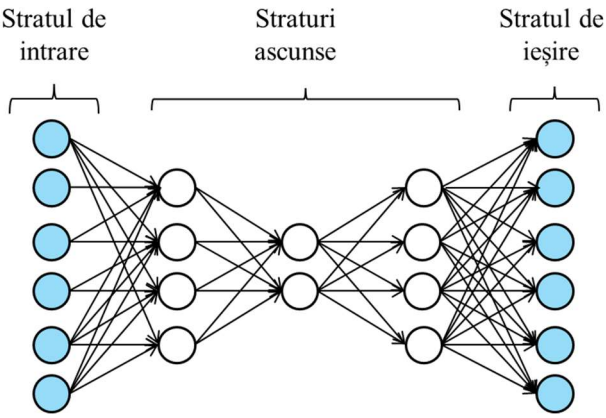


Fig. 2.2 *The general architecture of an autoencoder*

- *Security analysis*

In order to ensure an adequate level of safety in the operation of electricity systems, it is necessary to apply real-time methods of assessing the safety and the risk of triggering a collapse. Classical methods have the disadvantage of high computational effort, which leads to an unacceptable computational time for decision-making in a real-time system. To solve this challenge, recent techniques use artificial neural networks to assess the state of the system at a given time. al. [36] have studied the problem of identifying the oscillation mode of the transient regimes in the electrical power systems. Thus, they proposed a convolution neural network that receives phasorial measurements over time, classifying the transient regime based on this information into one of three categories: stable, unstable oscillatory or unstable aperiodic. The accuracy of the model on the analyzed test networks reached 97%, exceeding the performance obtained with other artificial intelligence techniques, such as decision trees, or vector-supported machines. Similarly, the paper [37] proposes the use of convolution neural networks for the evaluation of static state security. Being also a classification problem, the output of the neural network is represented by the level of security of the system regime: normal state, state of alert, state of emergency. The results showed a neural network accuracy of over 90% for all test networks studied. Bulac et. al. [38] developed an RNA-based program for assessing the risk of voltage instability in an electrical power system by conducting tests on the IEEE 30 network.

- *Fault location, isolatioan and restauration*

Another important challenge in the operation of power systems that can be solved with the help of neural networks is that of locating faults on a power line. Identifying the location is difficult, especially on cable lines, where the line is buried in the ground. In recent years, technologies based on DC power transmission have seen a significant increase in interest. [39] analyzes the problem of identifying the distance at which a defect occurred on a DC voltage

line with the help of convolution neural networks. The performance of the presented method is high, reaching maximum errors of the order of hundreds of meters. The paper [40] presents a neural network-based methodology for the identification of faults in distribution networks, obtaining promising results in terms of the estimated distance of fault site identification. The development of these techniques will lead to a reduction in costs and in the time it takes to identify and repair defects in power lines, thus increasing the degree of continuity in the supply to consumers, being an essential indicator in the operation of power grids. [41]

2.2. Clustering techniques

Artificial intelligence techniques in which data cannot be arranged in the form of input-output value pairs, with only input quantities, are part of the class of problems with unsupervised learning. The goal of algorithms in this class is to extract certain features from the dataset and use them later. The main type of problems that can be solved by unsupervised learning are clustering problems, which involve identifying similar input examples and grouping them into clusters. Applications of these clustering techniques include reducing the size of the problem and identifying certain characteristics of examples based on their similarity. Among the most commonly used clustering techniques are k-means, fuzzy c-means [42] and self-organizing SOM (Self Organizing Map) maps, also called Kohonen neural networks. [43]

2.2.1. k-means algorithm

The k-means method is one of the most widely used clustering techniques. This involves choosing a number of clusters, represented by a randomly distributed point in the search space, called centroids. The algorithm's iterative process will optimally distribute the location of the centroids so that they synthesize the essential features of the input data.

The first step of the algorithm is to choose the number of clusters. The goal of the algorithm is to minimize the objective function:

$$MIN\ J = \sum_{i=1}^{N}\sum_{j=1}^{C} a_{ij} \left\| x_i - c_j \right\|^2 \tag{2.1}$$

, where N is the number of data, C is the number of clusters. Notation $||x_i - c_j||^2$ represents the Euclidean distance between the x_i point and the center of the j cluster.

After the initialization of the centroids, for each point the distance from all the centroids is determined and the value is determined a_{ij}.

$$a_{ij} = \begin{cases} 1, \ dacă \ \left\| x_i - c_j \right\| \text{ este minim} \\ 0, \ \text{altfel} \end{cases} \qquad i=\overline{1, N}, j=\overline{1, C} \tag{2.2}$$

After assigning each point to a cluster, the position of the centroids is recalculated using the following equation:

$$c_j = \frac{\sum_{i=1}^{N} a_{ij} x_i}{\sum_{i=1}^{N} a_{ij}}, \quad \overline{j=1, C} \tag{2.3}$$

The k-means algorithm assumes the iterative application of equations (2.1)-(2.3) for a predetermined number of iterations or until the difference in the values of the objective function from two successive iterations is less than a threshold.

The major challenge when using clustering algorithms is choosing the optimal number of clusters [44]. For the k-means algorithm, one method for evaluating the number of clusters is the elbow method. This involves making the algorithm with multiple values for the number of clusters. The optimal option is considered to be the number of clusters from which the difference in performance becomes negligible.

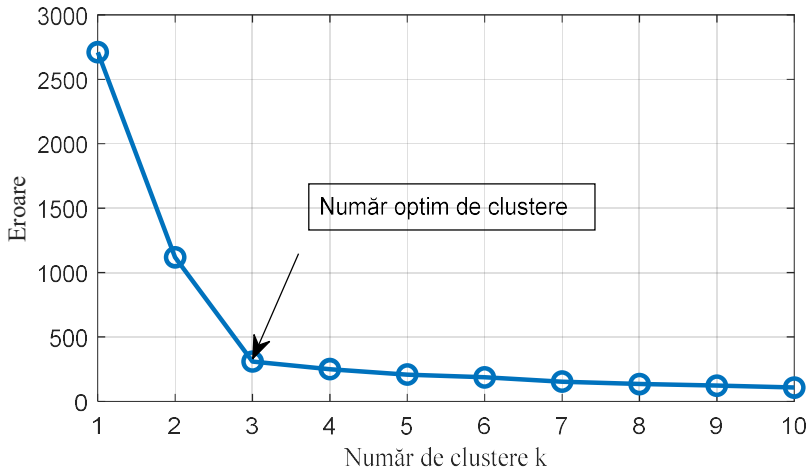


Fig. 2.3 Schematic of the elbow method

2.2.2. Fuzzy c-means

This method works similarly to the k-means algorithm, the technique also involving fuzzy logic that defines the notion of cluster membership. In the fuzzy c-means method, a point in the dataset no longer belongs to a single representative cluster, but belongs to all clusters with varying degrees of trust. The objective function is defined as follows:

$$MIN\ J = \sum_{i=1}^{N} \sum_{j=1}^{C} \mu_{ij}^{m} \left\| x_i - c_j \right\|^2 \tag{2.4}$$

, where μ_{ij} is the membership degree of x_i to cluster c_j, while m is the fuzzy parameter.

$$\mu_{ij}=\frac{1}{\sum_{k=1}^{N}\left(\frac{\left\|x_i-c_j\right\|^2}{\left\|x_i-c_k\right\|^2}\right)^{\frac{2}{m-1}}} \quad i=\overline{1,N}, j=\overline{1,C} \tag{2.5}$$

It is observed that μ_{ij} will have non-zero values for all C. This aspect gives greater flexibility to the algorithm compared to the k-means method, given that a point can belong to several clusters simultaneously [45].

The new positions of the centroids are calculated similarly to the k-means method:

$$c_j=\frac{\sum_{i=1}^{N}\mu_{ij}^m x_i}{\sum_{i=1}^{N}\mu_{ij}^m}, \quad \overline{j=1,C} \tag{2.6}$$

The main challenge of the fuzzy c-means method is choosing the optimal number of clusters, similar to the k-means method. Several performance indicators have been proposed in the literature [46].

Tabelul 2.2 Indicatori de performanță pentru algoritmul fuzzy c-means

Denumire indicator	Formulă de calcul	Obiectiv
Partition Coefficient (PC)	$PC=\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{C}\mu_{ij}^m$	Maximization
Modified Partition Coefficient (MPC)	$MPC=1-\frac{C}{C-1}\left(1-\sum_{i=1}^{N}\sum_{j=1}^{C}\mu_{ij}^2\right)$	Maximization
Partition Entropy (PE)	$PE=-\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{C}\mu_{ij}\ln(\mu_{ij})$	Maximization
Xie-Beni Coefficient (XB)	$XB=\frac{\sum_{i=1}^{N}\sum_{j=1}^{C}\mu_{ij}\left\|x_i-c_j\right\|^2}{N(\min\{c_i-c_k\})}$	Maximization

2.2.3. Clustering applications

In [49], the authors applied the k-means algorithm to identify residential consumer patterns, with the aim of developing demand response applications by local energy market operators. In the paper [50], the authors developed a data analysis technique based on clustering methods to identify energy theft in low-voltage power grids, identifying unusual patterns for various consumers. The accuracy of the proposed method was 96.73%, having a superior performance compared to traditional techniques. With the help of clustering techniques, Sanati et. al. [51] propose to streamline the operation of protections in a microgrid, by implementing an operating logic dependent on the location of the equipment in the network and the place of fault, reaching

a defect elimination speed of less than 500 ms. With the increased demand for electric vehicles, charging them is becoming a challenge in the operation of power grids. To reduce waiting times and balance the grid, the authors of the paper [52] propose grouping electric vehicle charging centers into clusters so that charging stations can have optimized scheduling according to the order and urgency of charging certain vehicles. Another current challenge in the energy field is the increase in the number of prosumers, which can produce overloads in low and medium voltage power grids. A common method for encouraging the flattening of the load curve is the implementation of demand response programs. In this regard, in [53] a clustering method based on the k-means technique was proposed, through which 6 consumption patterns for prosumers were identified, subsequently the implementation of a demand response program based on differentiated pricing according to the time of consumption was economically evaluated.

Due to the increasing amount of data collected from power systems, forecasting applications can use clustering techniques to preprocess data. In this way, more accurate forecasts can be made. In [54] the authors propose the clustering of historical consumptions using the fuzzy c-means method and the realization of a forecasting algorithm based on neural networks on each previously identified pattern. The proposed model achieves an average error of 2.15%, compared to 5.49% achieved with a model that uses only neural networks.

With the development of renewable energy sources, the energy market is changing and in many countries separate markets are being created depending on the area. G. Poyrazoglu [55] proposed the application of clustering techniques for segmenting the electricity market in Turkey, resulting in an optimal partitioning into 3 clusters.

2.3. Evolutionary computation

Evolutionary computational algorithms have recently become a popular alternative for solving complex optimization problems that introduce difficulties in solving by traditional deterministic methods. They represent a class of optimization methods based on various mechanisms and phenomena found in nature (e.g., the social behavior of various animal species), which find the optimal solution starting from a set of initial solutions, in an iterative manner.

The importance of integrating optimization algorithms in the operation and development of power systems is reflected in the high interest of the academic community in this field. At the same time, the use of optimization techniques based on artificial intelligence is becoming more and more frequent due to the performance of the algorithms recently proposed in the literature, as well as the technological advancement of hardware components, which allow solving computationally demanding problems. Fig. 2.6 shows the annual evolution of the publications indexed in the Google Scholar platform that address optimization problems in power systems.

There is a significant increase in the number of articles and books, registering 18000 publications in 2024, 16% more than the previous year and twice as many as in 2019.

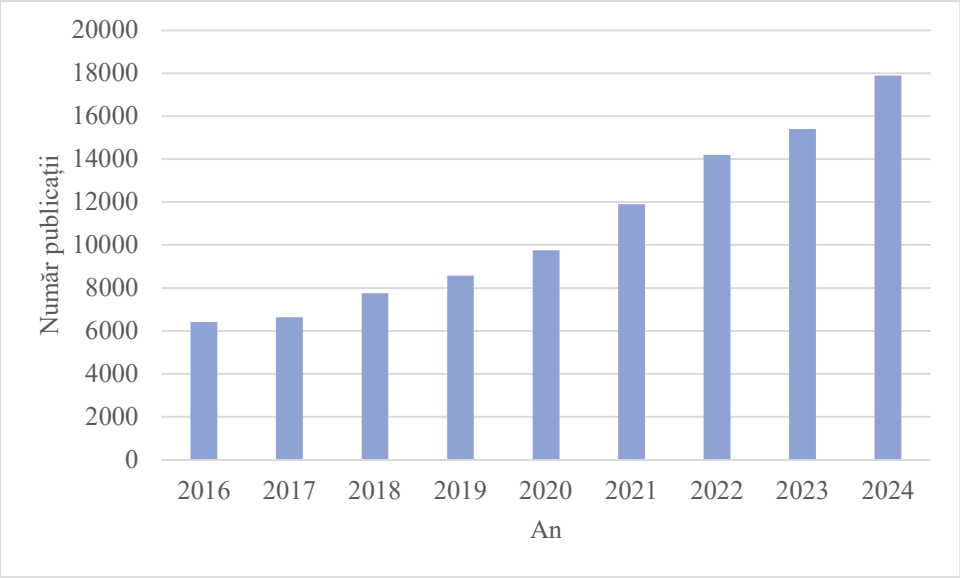


Fig. 2.4 Evolution of the number of publications indexed in the Google Scholar platform using the keywords "evolutionary computation" and "power systems"

2.3.1. Applications of evolutionary computation algorithms

The problems of optimizing power circulations are fundamental to ensure an economically efficient operation of electricity systems [56]. Technological advances in the field of electricity transmission (e.g. FACTS devices), as well as the emergence of new optimization algorithms in the literature have made these classic optimization problems of further increased interest.

- *Optimal reactive power dispatch and Optimal power flow*

The issue of Optimal reactive power dispatch is of high interest, due to the benefits that can be brought in the process of operating electrical networks. In this regard, numerous articles address this optimization problem using various solving techniques. Out of a total of 190000 articles published in this field, among the most common algorithms used are the Genetic Algorithm (AG), Particle Swarm Optimization (PSO), Evolutionary Differential Algorithm (ADE), Simulated Hardening (SA), Gray Wolf Algorithm (GWO), Ant Colony Optimization (ACO), and Whale Algorithm (WOA). Old-generation metaheuristic algorithms, such as AG, PSO, and SA, are among the most widely used in solving optimization problems. As can be seen in Fig. 2.7, they are used in more than 50% of the published works. However, due to the superior performance of next-generation algorithms, their usability to solve real-world optimization problems is increasing.

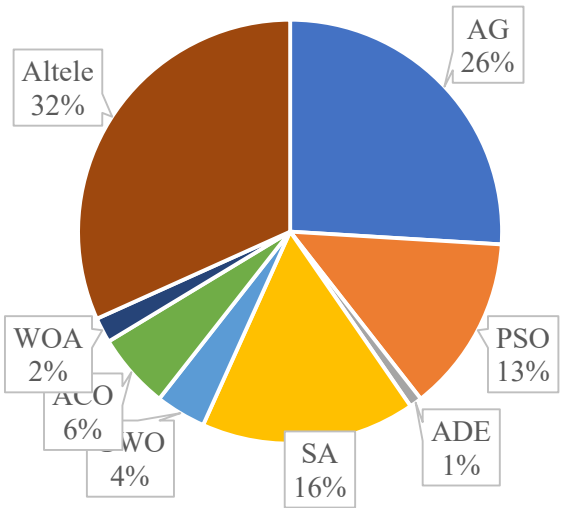


Fig. 2.5 Distribution of metaheuristic optimization algorithms used to solve the optimal reactive power distribution

In [57] the whale optimization algorithm is used to reduce active power losses by conducting a case study on Algeria's national power system. The paper [58] proposed a modified sine-cosine algorithm to increase the performance of the standard algorithm. The modified variant achieved 9% better results than the basic algorithm, when minimizing power losses was taken into account. Table 2.3 presents a brief taxonomy of publications that address the solution of the RDPA problem using metaheuristic optimization algorithms.

Tabelul 2.3 Taxonomy of scientific papers on the ORPD problem

Referința	**Electrical network type**	**Algorithm**	**Objective Function**	**Single objective / Multi objective**
Medani *et. al.* [57]	Transmission	Whale Optimization Algorithm (WOA)	ΔP	✓ / ✗
Abdel-Fatah *et. al.* [58]	Transmission	Modified Sine-Cosine Algorithm (M-SCA)	ΔP / U_{dev} / VSI	✓ / ✗
Aljohani *et. al.* [59]	Transmission	Particle Swarm Optimization (PSO)	ΔP / U_{dev} / VSI	✓ / ✓
Ela *et. al.* [60]	Transmission	Differential Evolution (DE)	ΔP / U_{dev} / VSI	✓ / ✗
Sidea *et. al.* [61]	Distribution	Particle Swarm Optimization (PSO)	ΔP / U_{dev}	✗ / ✓
Duman *et. al.* [62]	Transmission	Graviational Search Algorithm (GSA)	ΔP / U_{dev} / VSI	✓ / ✗

Sahli *et. al.* [63]	Transmission	Particle Swarm Optimization & tabu search (PSO-TS)	ΔP / U_{dev}	✓ / ✗
M. Basu [64]	Transmission	Differential Evolution (DE)	ΔP / U_{dev} / VSI	✓ / ✓
Sulaiman *et. al.* [65]	Transmission	Grey Wolf Optimizer (GWO)	ΔP / U_{dev}	✓ / ✗
Chen *et. al.* [66]	Distribution	Optimizarea cu roiuri de particule și logică fuzzy (fuzzy−PSO)	ΔP	✓ / ✗

ΔP – power losses minimization
U_{dev} – voltage deviation minimization
VSI – voltage stability index minimization

Unlike the ORPD, optimal power flow (OPF) optimization also addresses the optimization of active power circulation, in addition to reactive power, generally aiming to minimize the operating cost of an EEA (e.g., the cost of fuels in power plants). Traditionally, the OPF problem has been solved for transmission networks [67], [68]. With the development of electrical distribution networks and the concept of microgrid [69], the idea of coordinating the active network elements in order to obtain the lowest possible operating cost began to be addressed in the literature [70], [71]. Table 2.4 centralizes articles based on the use of metaheuristic methods to solve the OPF problem.

Table 2.4 Taxonomy on optimal power flow publications

Reference	**Electrical network type**	**Algorithm**	**Objective function**	**Single objective / Multi objective**
Vaisakh *et. al.* [67]	Transmission	Differential Evolution (DE)	F_c, U_{dev}, VSI	✓ / ✗
Mohamed *et. al.* [72]	Transmission	Moth Swarm Algorithm (MSA)	F_c, E_c, ΔP, U_{dev}, VSI	✓ / ✗
Duman *et. al.* [73]	Transmission	Gravitational Search Algorithm (GSA)	F_c,U_{dev}, VSI	✓ / ✗
Roy & Paul [74]	Transmission	Krill Optimizer (KOA)	F_c, U_{dev}, VSI	✓ / ✓
Adaryani *et. al.* [68]	Transmission	Ant Bee Colony (ABC)	F_c, E_c, ΔP, U_{dev}, VSI	✓ / ✗
Moradi *et. al.* [70]	Distribution	Hybrid harmony search-genetic algorithm (HS−GA)	F_c, U_{dev}, VSI	✓ / ✓
Nikmehr *et. al.* [75]	Microgrid	Particle Swarm Optimization (PSO)	O_c	✓ / ✗
Mohammad *et. al.* [71]	Microgrid	Firefly Algorithm (FA)	O_c	✓ / ✗

3.CONCLUSIONS

3.1. General Conclusion

With the development of AI-based techniques, the concern for their implementation in various technical fields has increased. With the digitalization of the energy sector, the volume, variety and speed of data that can be accessed has increased significantly, so artificial intelligence techniques become suitable for interpreting patterns and extracting features from data. In the doctoral thesis, two different directions of applications were addressed, on the one hand the use of neural networks in the forecasting of electricity consumption and on the other hand the optimal allocation of production capacities with the help of evolutionary computing techniques.

Electricity consumption forecasting is a vital tool in the operation and planning of power systems. Although this field has been studied in the past, the power of neural networks for processing and interpreting patterns is making consumption forecasting a return to the attention of the academic community. Throughout the doctoral studies, two periods with major changes caused by different phenomena have been identified. First of all, the period of the COVID-19 pandemic dramatically affected the behavior of society and moments of movement restrictions could be profiled, consequently also of stopping an important part of the economic activity, having major effects on energy consumption at national level. Secondly, with the massive incentive of users to become prosumers by installing photovoltaic panels and allowing injection into the grid, the energy produced by these users meant that at lunchtime on sunny days the consumption recorded in SCADA systems was significantly lower compared to similar days in previous years. Several neural network architectures were developed within the doctoral thesis, which include multilayer perceptron neural networks, LSTM cells and convolution neural networks. Following the case study, it was identified that the best performing model is the one based on convolution neural networks, due to the ability to extract features from chronologically close data. The neural network model proposed in this doctoral thesis was used and adapted to the needs of the stated moments of time, the performance being in both cases superior to the model used within Transelectrica. At the same time, the ability to automate the process becomes attractive, due to the need for fewer resources.

Against the backdrop of the declared goal of the European Union member states to reduce the dependence of the energy sector on fossil fuels by supporting private investors to build new production capacities based on renewable sources, the demand for such projects has increased in recent years, as the electricity grid in Romania is not prepared to allow the connection of all projects. Due to the difficulty of expanding and modernizing the electricity grids, generated by obtaining all the necessary authorizations and the high costs, the need to operate the system as close as possible to the maximum capacity has become urgent. In this regard, it is necessary to carry out complex studies for the optimal allocation of the available capacity in the electricity grid, so that no modernization or expansion works are necessary. To solve this problem, a mathematical model of the optimization problem was proposed. The proposed methodology

for optimal capacity allocation is carried out in two stages. In the first stage, the additional installed power in the grid is maximized taking into account the operating limits of the grid elements and the nodal voltages. Also, the voltage control capabilities in an electrical energy system are considered and their optimal management is achieved. The second stage of the methodology involves rearranging the powers determined in the first stage in order to reduce power losses. The methodology is compared with a strategy in which tension control is not used and with a random technique, the results showing that the proposed model provides robust results. Evolutionary calculation techniques were used to solve the problem.

The proposed optimization algorithm is based on the marine scorpion algorithm, whose mechanisms are inspired by the behavior of the salp, a species of jellyfish-like invertebrates, in the process of foraging. Optimization methods based on evolutionary computing techniques have advantages over deterministic methods, such as computational speed and adaptability to complex problems without detailed modeling of the operating equations. Starting from the standard optimization algorithm, multiple improvements have been made to increase performance, the improved version being tested in the first phase on mathematical optimization functions, and the method will be tested to solve the problem of optimal distribution of reactive power, the results being superior to other algorithms frequently used in the literature.

3.2. Contributions

The main contributions of the doctoral thesis are set out below.

a) *Conducting a literature study* on the current state of artificial intelligence-based applications in the energy field;

b) Analysis of the factors influencing electricity consumption, thus identifying the need to adapt the forecast models to the current socio-economic context;

c) Implementation of a model based on neural networks for forecasting electricity consumption at the level of SENs, carried out in a first stage during the COVID-19 pandemic, later the model being adapted to manage the influence brought by prosumers;

d) *Proposing an optimization algorithm based on evolutionary computing techniques*. The proposed model starts from the standard variant of the marine salting algorithm, for which new mechanisms have been proposed, such as counterexample learning, introduction of a new type of salt, as well as crossing and mutation. The validation of the algorithm's performance was carried out based on several reference functions in the field of optimizations;

e) *Evaluation of the performance of the proposed algorithm in solving the problem of optimal reactive power distribution* for two test networks. Both single-objective and multi-criteria optimization (minimizing power losses while reducing voltage deviations from a reference value) were considered;

f) Development of an optimization model for the optimal allocation of available capacity in an electricity grid to ensure maximum power that can be additionally installed in an electricity system without the need for network modernization or expansion works, which propose major investments;

g) Dissemination of research results in multiple national and international conferences as well as in international journals during the doctoral internship.

Published paper in international journals

1. N. Anton, C. Bulac, B. Dobrin, **A. Tudose** – „Optimal Placement Of Phasor Measurement Units Using Multi-Criteria Analysis", *U.P.B. Sci. Bull., Series C*, **Vol. 86**, Iss. 4, 2024, WOS: 001380943300028.
2. **A.M. Tudose**, D.O. Sidea, I.I. Picioroaga, N. Anton, C. Bulac – „Increasing Distributed Generation Hosting Capacity Based on a Sequential Optimization Approach Using an Improved Salp Swarm Algorithm", *Mathematics*, **12(1)**, 48, Dec. 2023, DOI: 10.3390/math12010048, WOS: 001140674900001.
3. I. Picioroaga, M. Luca, **A. Tudose**, D. Sidea, M. Eremia, C. Bulac – "Resilience-Driven Optimal Sizing of Energy Storage Systems in Remote Microgrids", *Mathematics*, **15(22)**, 16002, Noi. 2022, DOI: 10.3390/su152216002, WOS: 001113328600001.
4. D.O. Sidea, **A.M. Tudose**, I.I. Picioroaga, C. Bulac – „Two-Stage Optimal Active-Reactive Power Coordination for Microgrids with High Renewable Sources Penetration and Electrical Vehicles Based on Improved Sine−Cosine Algorithm", *Mathematics*, **11(1)**, 45, Dec. 2022, DOI: 10.3390/math11010045, WOS: 000909656200001.
5. I. I. Picioroaga, **A. M**.**Tudose** , D. O. Sidea, C. Bulac – „Supply Restoration in Active Distribution Networks Based on Soft Open Points with Embedded DC Microgrids". *Mathematics*, **10(2)**, 211, Ian. 2022, DOI: 10.3390/math10020211, WOS: 000746279600001.
6. I. Picioroaga, **A. M. Tudose**, D. Sidea, C. Bulac, L. Toma – „Power Supply Restoration in Active Distribution Networks with High Photovoltaic Penetration Based on Soft Open Points". *Revue roumaine des sciences techniques-serie electrotechnique et energetique*, **66(3)**, 181-186, Dec. 2021, WOS: 000738293800001.
7. **A. M. Tudose**, I. I. Picioroaga, D. O. Sidea,, C. Bulac and V. Boicea, "Short-term load forecasting using convolutional neural networks in COVID-19 context: The Romanian case study", *Energies*, **vol. 14**, Iul. 2021, DOI: 10.3390/en14134046 WOS: 000672003000001.
8. **A. M. Tudose**, I. I. Picioroaga, D. O. Sidea, and C. Bulac, " NEURAL NETWORKS APPLICATION IN SHORT-TERM LOAD FORECASTING", *The UPB Scientific Bulletin, Series C*, **vol. 83**, no. 2, Iun. 2021, WOS: 000692193500018
9. **A. M. Tudose**, I. I. Picioroaga, D. O. Sidea, and C. Bulac, "Solving Single- and Multi-Objective Optimal Reactive Power Dispatch Problems Using an Improved Salp Swarm Algorithm," *Energies*, **vol. 14**, no. 5, p. 1222, Feb. 2021, DOI: 10.3390/en14051222, WOS: 000628120100001.

Published papers in international conferences

1. R. Micu, **A. Tudose**, A. Iantoc, I. Picioroaga, C. Bulac, „Electricity Price Forecasting on Day Ahead Market via a Multivariate CNN-LSTM Model", 2024 IEEE International Conference And Exposition On Electric And Power Engineering (EPEi), Iasi, Romania, oct. 17-19 2024, DOI: 10.1109/EPEi63510.2024.10758141.
2. I. Picioroaga, **A. Tudose**, D. Sidea, M. Calin-Arhip, „The Optimal Placement and Sizing of Soft Open Points to Enable Distributed Generation Hosting in Southern Romania", 2024

59th International Universities Power Engineering Conference (UPEC), Cardiff, Țara Galilor, 2-6 sep. 2024, DOI: 10.1109/UPEC61344.2024.10892422.

3. D.O. Sidea, **A.M. Tudose**, I.I Picioroagă, N. Anton, C. Bulac, „Performace Comparison of Metaheuristic Algorithms on Solving the Optimal Power Flow in a Active Distribution Network", 2023 11th International Conference on ENERGY and ENVIRONMENT (CIEM), București, Romania, 26-27 oct. 2023, DOI: 10.1109/CIEM58573.2023.10349771
4. D.O. Sidea, I.I. Picioroagă, **A.M. Tudose**, C. Podar, N. Anton, C. Bulac, "Optimal reactive power dispatch considering load variation in distribution networks using an improved sine-cosine algorithm", 2022 International Conference and Exposition on Electrical And Power Engineering (EPE), Iași, Romania, 20-22 oct. 2022, DOI: 10.1109/EPE56121.2022.9959076.
5. **A. Tudose**; R. Micu; I. Picioroaga; D. Sidea; A. Mandis; C. Bulac, „Power Systems Security Assessment Based on Artificial Neural Networks", 2022 International Conference and Exposition on Electrical And Power Engineering (EPE), Iași, Romania, 20-22 oct. 2022, DOI: 10.1109/EPE56121.2022.9959761
6. V.A. Ion; E.E. Gemil; M. Arhip-Calin; **A. Tudose**; N. Anton; G. Serițan, "A Survey of microgrid operation influence on power quality", 2022 57th International Universities Power Engineering Conference (UPEC), Istanbul, Turcia, 30 aug.-02 sep. 2022, DOI: 10.1109/UPEC55022.2022.9917884, WOS: 000886926200086
7. D.O. Sidea, **A.M. Tudose**, I.I. Picioroagă, L. Toma, C. Bulac, „Adapted Grey Wolf Optimizer for Dynamic Economic Dispatch in a Hybrid Microgrid", 10th International Conference on ENERGY and ENVIRONMENT (CIEM), București, România, 14-15 Oct., 2021, DOI: 10.1109/CIEM52821.2021.9614704.
8. I. I. PICIOROAGA, **A. M. TUDOSE**, D. O. SIDEA, C. BULAC and L. TOMA, "Application of Soft Open Points for Increasing the Supply Restoration in Active Distribution Networks," 2021 12th International Symposium on Advanced Topics in Electrical Engineering (ATEE), 2021, pp. 1-6, DOI: 10.1109/ATEE52255.2021.9425287, WOS: 000676164800131
9. I. I. Picioroaga, **A. Tudose**, D. O. Sidea, C. Bulac and M. Eremia, "Two-level Scheduling Optimization of Multi-microgrids Operation in Smart Distribution Networks," 2020 International Conference and Exposition on Electrical And Power Engineering (EPE), 2020, pp. 407-412, DOI: 10.1109/EPE50722.2020.9305614**.**
10. D. O. Sidea, I. I. Picioroaga, **A. M. Tudose**, C. Bulac and I. Tristiu, "Multi-Objective Particle Swarm optimization Applied on the Optimal Reactive Power Dispatch in Electrical Distribution Systems," 2020 International Conference and Exposition on Electrical And Power Engineering (EPE), 2020, pp. 413-418, DOI: 10.1109/EPE50722.2020.9305548.
11. **A. M. Tudose**, D. O. Sidea, I. I. Picioroaga, V. A. Boicea and C. Bulac, "A CNN Based Model for Short-Term Load Forecasting: A Real Case Study on the Romanian Power System," 2020 55th International Universities Power Engineering Conference (UPEC), Torino, Italy, 2020, pp. 1-6, DOI: 10.1109/UPEC49904.2020.9209768, WOS: 000627771000011

3.3. Future work

The future research directions aim to continue both the studies presented in the doctoral thesis and to address new topics essential for the transition of the energy sector towards an increased share of renewable production capacities:

- Improving the energy consumption forecasting algorithm by using advanced *Deep Learning* techniques, such as ensemble methods;
- Applying the algorithm for optimal capacity allocation for the electricity system in Romania and identifying measures to create a sustainable framework for the installation of new energy production sources. It is also proposed the statistical analysis of production from renewable sources, in order to identify the optimal energy mix;
- Analysis of the influence of storage facilities in the SEN, both from the point of view of the operation of the electricity grid and from the economic point of view.

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Cuprinsul tezei de doctorat

1. Introducere 10

2. Stadiul actual al utilizării algoritmilor bazați pe inteligență artificală în domeniul energetic 13

2.1. Rețele neuronale artificiale 13
2.1.1. Aplicații ale rețelelor neuronale în monitorizarea și controlul sistemelor electroenergetice 14
2.2. Tehnici de clusterizare 19
2.2.1. Algoritmul k-means 19
2.2.2. Algoritmul fuzzy c-means 20
2.2.3. Rețele neuronale Kohonen (Hărți cu auto-organizare) 21
2.2.4. Aplicații ale tehnicilor de clusterizare 23
2.3. Algoritmi bazați pe tehnici de calcul evolutiv 24
2.3.1. Aplicații ale algoritmilor de optimizare metaeuristici în monitorizarea și controlul sistemelor electroenergetice 25
2.4. Logica fuzzy 28
2.4.1. Aplicațiile logicii fuzzy în monitorizarea și controlul sistemelor electroenergetice 29

3. Rețele Neuronale Artificiale 32

3.1. Rețele neuronale artificiale de tip perceptron multistrat 32
3.2. Rețele neuronale recurente (RNR) 32
3.3. Rețele neuronale cu memorie de scurtă durată persistentă (LSTM) 33
3.4. Rețelele neuronale de convoluție 35
3.5. Funcții de activare 37
3.6. Algoritmul de antrenare a rețelelor neuronale 39
3.7. Metode de îmbunătățire a performanței rețelelor neuronale 40

4. Prognoza consumului de energie electrică utilizând concepte deep learning 43

4.1. Aspecte generale privind progrnoza consumului de energie electrică 43
4.1.1. Clasificare a problemelor de prognoză în funcție de orizontul de timp 43
4.1.2. Factori de influență asupra consumului de energie electrică 44
4.2. Efectele pandemiei COVID-19 asupra consumului de energie electrică 47
4.3. Modele propuse pentru prognoza consumului de energie electrică la nivel național 49
4.3.1. Selectarea datelor de intrare 50
4.4. Antrenarea și evaluarea modelului bazat pe RNA 52
4.4.1. Regresie liniară multiplă 53
4.5. Studiu de caz 53
4.5.1. Descrierea setului de date 53
4.5.2. Evaluarea performanței modelului propus 54
4.5.3. Reevaluarea modelului pentru anul 2025 61

5. Algoritmi de optimizare bazați pe tehnici de calcul evolutiv 69

5.1. Algoritmii genetici 70
5.2. Optimizarea cu roiuri de particule (Particle Swarm Optimization) 72
5.3. Algoritmul furnicilor leu (Ant Lion Optimizer) 74
5.4. Algoritmul salpului (Salp Swarm Algorithm) 74
5.4.1. Algoritmul salpului marin pentru probleme de optimizare cu un singur obiectiv 74
5.4.2. Algoritmul Salpului Marin pentru probleme de optimizare multicriterială 75
5.5. Îmbunătățiri propuse Algoritmului Salpului Marin 77
5.5.1. Tehnica de învățare prin contraexemplu 77

5.5.2. Ierarhia socială și implementarea salpilor exploratori ... 77
5.5.3. Operatori de încrucișare și de mutație ... 78
5.5.4. Mecanismul supraviețuirii celui mai adaptat ... 78
5.6. Validarea algoritmilor de optimizare ... 79

6. Rezolvarea problemei repartiției optime a puterii reactive ... 81

6.1. Aspecte generale privind repartiția optimă a puterii reactive în sistemele electroenergetice ... 81
6.2. Formularea problemei ... 82
6.2.1. Funcții obiectiv ... 82
6.2.2. Restricții de egalitate și inegalitate ... 84
6.3. Studiu de caz ... 85
6.3.1. Validarea metodei de calcul a regimului permanent ... 85
6.3.2. Descrierea setului de date ... 86
6.3.3. Rezultatele repartiției optime a puterii reactive considerând un singur obiectiv ... 88
6.4. Rezultatele repartiției optime a puterii reactive considerând optimizare multicriterială ... 95

7. Alocarea optimă a capacității disponibile de racordare a surselor de energie în rețelele electrice ... 98

7.1. Creșterea gradului de integrare a surselor regenerabile de energie ... 98
7.1.1. Considerente generale ... 98
7.1.2. Metode de creștere a gradului integrare a surselor regenerabile în rețelele electrice ... 99
7.1.3. Reducerea temporară a producției ... 99
7.1.4. Managementul sarcinilor ... 100
7.1.5. Monitorizarea în timp real a capacității de transport a liniilor electrice ... 103
7.1.6. Instalații de stocare ... 103
7.1.7. Investiții de modernizare a rețelei eletrice ... 104
7.1.8. Reglajul tensiunii ... 106
7.2. Formularea problemei ... 106
7.2.1. Funcții obiectiv ... 106
7.2.2. Restricții de egalitate și inegalitate ... 107
7.2.3. Adaptarea modelului matematic pentru algoritmi de calcul evolutiv ... 108
7.3. Studiu de caz ... 109
7.4. Rezultatele problemei de creștere a gradului de integrare a noilor surse ... 113
7.4.1. Rezultatele primei etape ... 113
7.4.2. Rezultatele celei de-a doua etape ... 116

8. Concluzii finale ... 119

8.1. Concluzii generale ... 119
8.2. Contribuții ... 120
8.3. Perspective de dezvoltare a cercetării ... 123

Bibliografie ... 124