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Model for Forecasting of Electricity Losses During Transmission and Distribution in an Electricity System

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Abstract - *The forecasting of losses in a country's electrical system is an important factor for its optimal management. It allows for the planning of the appropriate amount of electricity that must be produced in order to meet the needs of the economic sector and household customers. A portion of the electricity losses can be forecasted and assessed. This includes losses caused by technical components for transmission and distribution of electricity, losses from power lines formed by the length, cross-section, or resistance of conductors, the corona effect, losses due to no load or light load of the transformers, energy consumption for the needs of the individual units in the electricity system, etc. Another portion of the losses is not subject to accurate calculation. These are losses from accidents on significant lines, which may be due to wear and tear of the equipment being used, natural disasters, changes in the prevention programs, or even illegal or dishonest consumption of electricity, etc. These losses cannot be forecasted by standard statistical methods or well-known formulas. This article presents a study for forecasting electricity losses by using neural networks. Experiments have been conducted related to the forecast of the losses of the electricity system in Bulgaria.*

Keywords — *electrical power losses, power transmission losses, power system losses, forecasting of electricity losses.*

I. INTRODUCTION

The forecasting of electricity losses is an essential element of the successful management of a country's electricity system. This allows for more efficient planning and management of the energy produced. Part of the losses caused by the technical components for transmission and distribution of electricity can be calculated with relatively high accuracy using standard formulas for technical losses. Such are the losses from the power lines, formed by the length, cross-section or resistance of the conductors, the corona effect, idle losses or losses due to light load of the transformers, the energy consumption for the needs of the individual units in the electricity system (ES), etc. Of course, to save primary energy resources and free up additional generator power, the goal of the management of the national electricity system (NES) is to reduce these losses by applying various organizational and technical optimizations.

An important component of the total losses that cannot be calculated in the formulas for technical losses are caused by stochastic components, such as accidents, dishonest consumption, the need for unplanned diversions of energy flows, a drastic change in weather conditions that may affect both the power flow and the specific resistance of the lines, subjective and random operator errors, etc. Electricity theft has become an increasingly important factor in recent years due to the growing popularity of cryptocurrencies. According to Cambridge Bitcoin Electricity Consumption Index, the electricity consumed annually for bitcoins mining worldwide exceeds 120 TWh and is commensurate with the consumption of countries such as Sweden, Ukraine, Argentina, Norway, and others [1]. In some cases, crypto miners invent bold and large-scale ways to steal electricity. Due to stochastic components, the actual reported losses at the end of a given period often exceed the forecasted technical losses.

The goal of the present study is to create a loss-forecasting model which includes both losses from technical elements and losses from unforeseen events and processes. Its implementation is based on the use of artificial neural networks. The model is experimented with to forecast the losses in the electricity system of Bulgaria.

II. TECHNICAL LOSSES IN TRANSMISSION AND DISTRIBUTION OF ELECTRICITY

Technical losses in the power system can be calculated with relative accuracy. Standard formulas are used for components such as losses in power lines and transformers.

Losses in power lines form a large portion of the total technical losses. They are calculated by the following formulas [2]:

$$\Delta P = 3\left(\frac{S}{U_n\sqrt{3}}\right)^2 R,\ [W] \text{ or}$$
$$\Delta P = 3I^2 R, [W], \text{ where:}$$

- S is the transmitted power measured in kVa;
- U_n is the nominal voltage of the power line, kV;

- R – the resistance of one phase, Ω;
- I- the flowing current, A.

Keeping in mind that

$$R = \frac{\rho L}{A},$$

Where ρ, L and S are respectively the specific resistance, the length, and the cross-section of the conductor, it becomes clear that the transmission losses are directly related to the specific resistance of the materials used. This imposes some trade-offs between losses and the cost of materials with a lower resistance value [3]. In this direction, numerous studies of the resistance have been carried out [4], [5], sometimes reaching the sphere of superconductors at low temperatures, influencing their almost zero resistance [6], as well as that with higher temperatures [7].

The conversion of electrical voltage in transformers also causes losses [2]. According to the Joule-Lenz law, the power losses in the copper of the transformer are proportional to the square of the current I, flowing through the coils. For a three-phase transformer:

$$\Delta P_c = 3I^2 R_t \text{ or}$$

$$\Delta P_c = \frac{S_n^2}{U_n^2} R_t, [kW], \text{ where}$$

- R_t is the active resistance of the coil of one phase of the transformer, Ω;
- I- the flowing current, A.

Numerous formulas for ***calculating losses in electric motors, generators, busbar losses, power failure losses***, etc., are described in the scientific literature [2], [8].

III. OTHER FACTORS FOR ELECTRICITY LOSS

In addition to the technical losses discussed above, there are those that are not subject to accurate calculation and whose values are based only on statistics. These are losses from ***accidents*** on significant lines, which may be due to ***wear and tear of used equipment***, ***natural disasters***, ***change in prevention programs***, or even ***illegal or dishonest consumption of electricity***.

The extraction of cryptocurrencies stimulates the consumption of electricity, which is a major resource for their mining. The annual electricity consumption for bitcoins mining worldwide exceeds 120 TWh. For comparison, the annual energy consumption of the largest consumer countries is – China - over 6400 TWh, the USA - around 4000 TWh, India - over 1200 TWh, and Russia - around 1000 TWh. [1] (fig. 1). The desire of crypto miners to get rich easier and faster stimulates some of them to invent bold and large-scale ways to ***steal electricity***, which leads to increased production losses. Establishing mechanisms for the immediate detection of electricity theft would drastically reduce losses of this kind.

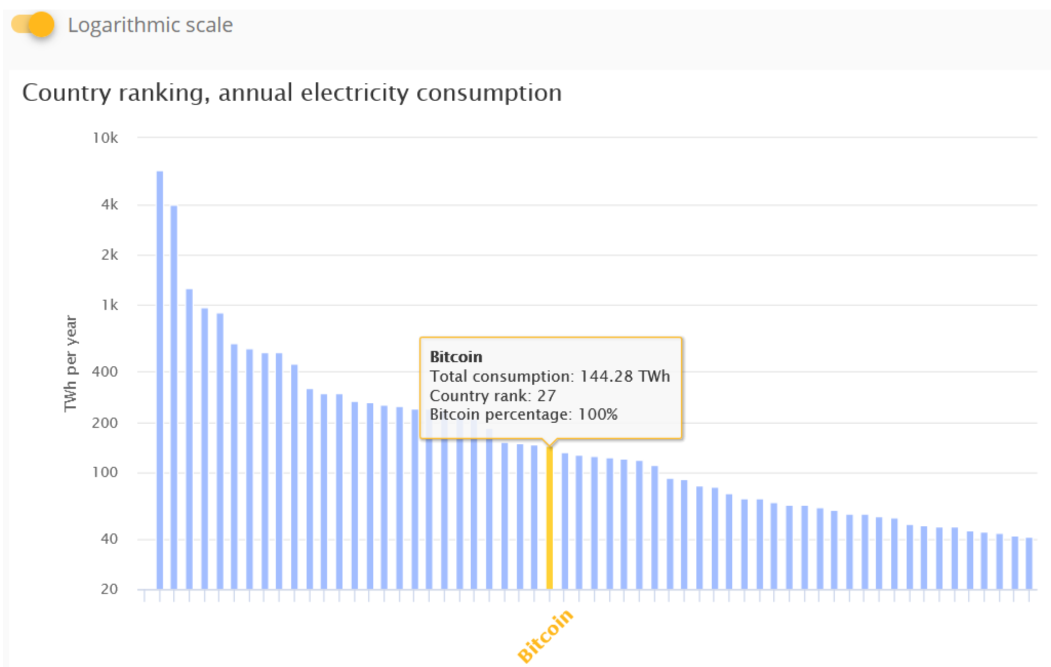

Fig. 1: Electricity consumption of countries with high electricity consumption compared to global electricity consumption for bitcoins mining (on an annual basis)

Another factor for losses in an energy system is the incorrect planning of the produced electricity. ***Overproduction of energy***, for example, again leads to losses due to produced but unused and therefore unpaid energy. In these cases, it is necessary ***to turn off large production facilities to compensate for the frequency in the system***.

Due to the unpredictability and random nature of this type of power loss factor, they cannot be estimated in advance with standard methods of forecasting analysis and assessment. Most of the formulas lose their predictive significance after the stochastic processes in the distribution are added.

In general, these energy losses are complex in nature and can be represented by the following formula [9]:

(1) $\Delta W = \Delta Pt\ [kWh]$, where

- ΔW are the losses of active electricity, kWh;
- ΔP is the loss of active power, kW;
- t – is the time period for which the losses are calculated.

Formula (1) is valid only when the power transmitted by the power line, for example, is constant for the entire period of time. Unfortunately, the consumers' load is usually not constant over time. This means that the power transferred is also variable [9]. The exact determination of the losses, in this case, is very difficult due to the fact that the variable load is a complex function of time, which in the most general form can be represented as follows:

$$\Delta W = \int_{t_1}^{t_2} \Delta P(t)dt.$$

This leads to an additional financial burden both on the energy producers themselves and their suppliers and on the end-user. Therefore, it is important for all parties involved to find a way to reduce losses.

Better understanding and management of network losses is an important prerequisite for saving huge financial resources, reducing prices for end-users, even the possibility of introducing new environmental solutions related to production and transmission, which have so far been unreasonable as an investment. That is why the efforts of many researchers are focused on this component of the work of national electricity systems.

Some researchers use formulas to calculate energy losses. Such are the developments of [11], which focus on losses due to corona-effects:

$$L_{Corona} = 242^{\frac{(f+25)}{\delta}} \sqrt{\frac{r}{d}} (V - V_0)^2 . 10^{-5} kW$$

Calculated in phases for each kilometer of the line. Here:

- f is the voltage frequency;
- δ is a factor related to air density;
- r and d are respectively the cross-sections of the conductors and the distance between them;
- $V and\ V_0$ are the operating and destructive voltage.

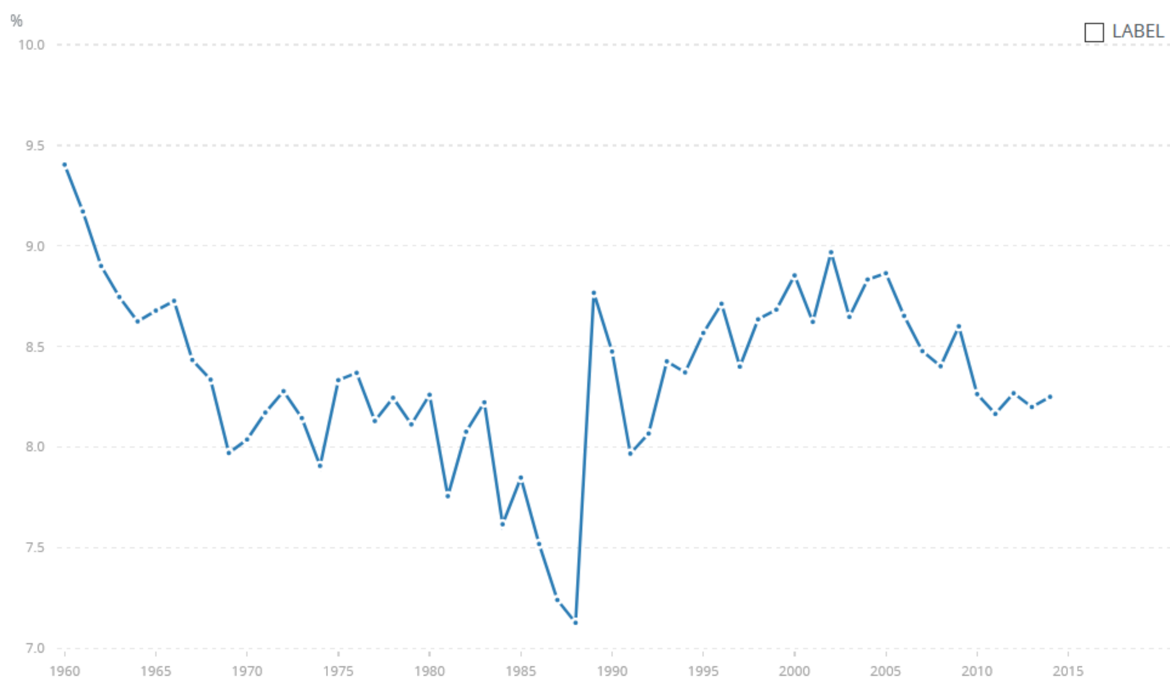

Fig. 2: World electric power transmission and distribution losses (% of output)

IV. APPROACHES TO FORECASTING LOSSES IN TRANSMISSION AND DISTRIBUTION SYSTEMS

Although there is a clear downward trend, worldwide electricity losses during transmission and distribution remain in the range of 8-9% of the amount produced [10] (fig. 2).

When the experts add ohmic losses to this:

(2) $L_{ohmic} = I^2 R$

and taking into account the resistance of the conductors ρ, its length L, and its cross-sectional area A, the final losses are calculated by the equation:

$$T = l^2 \frac{\rho L}{A} + 242^{\frac{(f+25)}{\delta}} \sqrt[4]{\frac{A}{\pi d^2}} (V - V_0)^2 . 10^{-5} kW$$

An approach involving formulas was used in [12], where the losses are calculated using formula (2), but also taking into account the air temperature, the length, and the resistance of the conductors. On the other hand, in [13], an approach was chosen for separate calculation of operating losses of a single transformer:

$$\Delta P_{trans} = \Delta P_{N-LL} + \Delta P_{LL} \frac{S^2}{S_{nom}^2}$$

and two transformers operating in parallel:

$$\Delta P_{trans} = n \Delta P_{N-LL} + \frac{1}{n} \Delta P_{LL} \frac{S^2}{S_{nom}^2}$$

By making comparisons and drawing conclusions about the efficiency of operation and the reduction of idle losses of transformers, in both cases:

- ΔP_{N-LL} are the idle losses of the transformers (no-load losses);
- ΔP_{LL} are the losses when connected in light load (load losses);
- n is the efficiency ratio (efficiency factor);
- S and S_{nom} are respectively the operating and the nominal power (load power);

Similar techniques, involving the use of known formulas or inferences thereof, are used by [14], [15], [16], [17], etc.

However, all the cited cases, despite their accuracy in calculating the theoretically predicted losses, have one common drawback. They cannot cope with the stochastic component in the composition of total losses, which manifests itself in various forms – accidents, dishonest consumption, and theft, sudden need for redirection of energy flows, abrupt change of meteorological conditions, subjective and random operator errors, etc. For this reason, the reported electricity losses at the end of a given period often exceed those calculated in advance using mathematical formulas.

V. FORECASTING OF ELECTRICITY LOSSES IN TRANSMISSION AND DISTRIBUTION SYSTEMS USING ARTIFICIAL NEURAL NETWORKS

The human brain contains about 25 billion nerve cells - neurons [18] (fig. 3). They communicate with each other in various chemical, electrical or mixed ways through their synapses [19]. Each neuron receives signals through its dendric system – the input part of the neuron. It has the form of a dense network of cells outgrowths with a tree-like structure. Here is the main network for delivering information to the neuron. The body of the neuron consists of a nucleus, cytoplasm, and various organelles that help in the synthesis and transport of neurotransmitter molecules. The axon is the longest outgrowth of the neuron. The length of the axon can exceed tens of thousands of times the diameter of the cell body. The axon outputs nerve impulses from the cell body, transmitting information to another cell. Finally, the structure of the neuron ends with the corresponding synapse, making the connection between its axon and the dendritic system of another neuron.

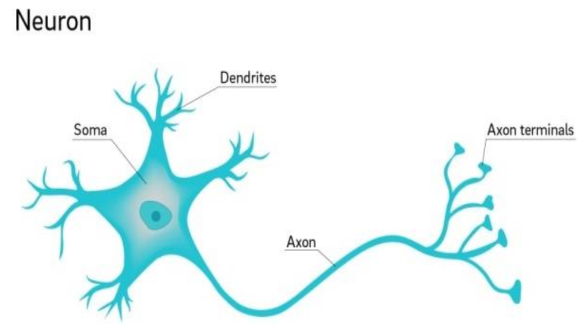

Fig. 3: Neuron structure

Following the evolutionarily created model, the structure of the artificial neuron is represented schematically according to fig. 4. Here

- $\vec{X}(x_1, x_2, x_3, \ldots, x_n)$ is the vector if input stimuli;
- $\overrightarrow{W}(w_1, w_1, w_2, \ldots, w_n)$ is the weight vector;
- b – the threshold of the neuron;
- S – the function modeling the summation of input stimuli;
- g – the activation function modeling the axon output signal.

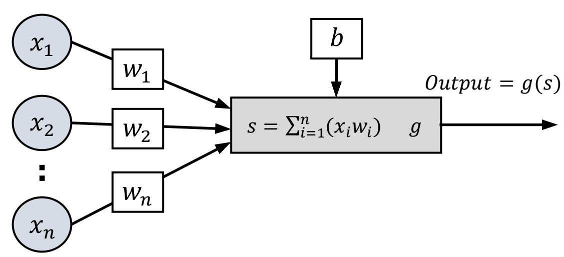

Fig. 4: Artificial neuron model

To forecast the losses in the transmission and distribution systems of NES of Bulgaria, a model has been created in the MatLab environment [20]. A neural network with straight signal propagation was used. For sources from which were formed the input-output samples for network training, data from the official information on the overall energy balance of Bulgaria were used [21] and the information system of the National Statistical Institute [22] for the period 2008-2018. For the assessment of the forecast quality of the network, data from 2019 from the same sources were used.

TABLE 1 TRANSFER FUNCTIONS AND ALGORITHMS USED FOR NEURAL NETWORK TRAINING

Transfer functions	Algorithms for training
Hyperbolic tangent sigmoid transfer function	Levenberg-Marquardt
Log-sigmoid transfer function	Bayesian Regularization
Hard-limit transfer function	Scaled Conjugate Gradient
A symmetric hard-limit transfer function	BFGS Quasi-Newton
Competitive transfer function	Resilient Backpropagation
Elliot symmetric sigmoid transfer function	Conjugate Gradient with Powell/Beale Restart
Elliot 2 symmetric sigmoid transfer function	Fletcher-Powell Conjugate Gradient
Inverse transfer function	Polak-Ribiére Conjugate Gradient
Positive linear transfer function	One Step Secant
Radial basis transfer function	Variable Learning Rate Backpropagation
Normalized radial basis transfer function	
Saturating linear transfer function	
Symmetric saturating linear transfer function	
Soft max transfer function	
Triangular basis transfer function	

Several different transfer functions and training algorithms have been used in the training (table 1). They are combined automatically to find the wanted neural network, interpolating the most successful development of losses in the specified period (2000-2018) and showing the smallest error in forecasting for 2019.

After the experiment, a network was constructed, trained with 208 iterations by the method of Bayesian regularization. Its interpolation ability on all training samples is shown in fig. 5. The registered interpolation error is 0.13 thousand tonnes of oil equivalent (toe).

The architecture of the network consists of a hidden layer containing 17 neurons and one output neuron, which form the value of electricity losses. The transfer function in the body of the neurons in the hidden layer is tangent-hyperbolic, and in the output neuron – the linear function $f(x) = x$ (fig. 6).

For 2019, the neural network predicted the value of losses of 239.6913 thousand toe, with a real amount of loss in the national electricity system of 237.9 thousand toe. The absolute forecast error is 1.7912 thousand toe. The constructed neural network showed that a gradual reduction of losses in the energy system is expected, as the forecasting error for the next year is estimated at 2 thousand toe. The

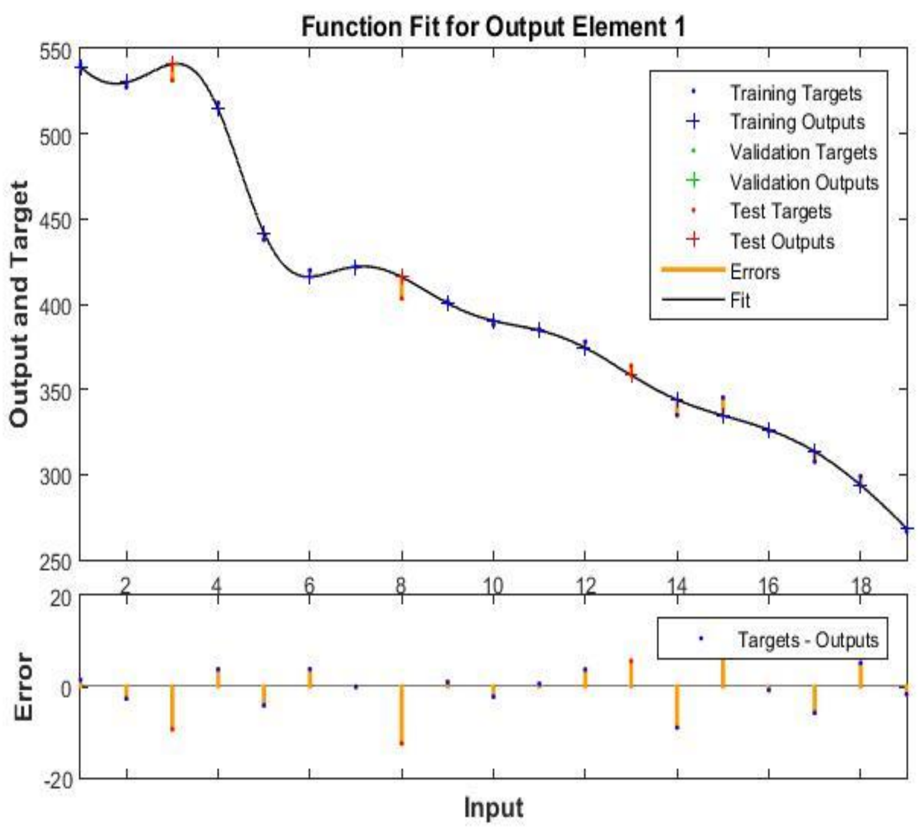

Fig. 5: Interpolation of input data

neural network was used to forecast electricity losses for the period 2020-2024. In this case, the neural network forecasts a gradual reduction of the lost amount of electricity to values in the order of 120 thousand toe for 2024 (table 2).

TABLE 2 ESTIMATED LOSSES IN NES OF BULGARIA FOR D 2020-2024

Year	Estimated losses in thousands toe
2020	210.3679
2021	182.6024
2022	157.9155
2023	137.0924
2024	120.2808

One main reason for the modeled structures to report a reduction in losses is probably the trend they have captured to increase energy efficiency among end customers, in the industrial sector of Bulgaria, as well as in the electricity system of the country as a whole. This trend is confirmed by another study of ours [23].

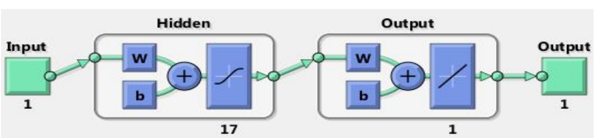

Fig. 6: Neural network architecture

VI. CONCLUSION

Standard formulas can be used to calculate a large part of the losses in the electricity transmission and distribution network caused by the technical components. These are losses related to the conversion of part of the energy into heat, losses in magnetic conductors, losses caused by temperature changes, losses that can be defined by the energy flow. But apart from them, there is one component that is very difficult to predict and assess accordingly. There are additional technical reasons such as accidents, accidental changes in the direction of flows, change in the schedule of repairs, non-technical components such as illegal consumption, subjective operator errors, etc. Therefore, in most cases, the pre-calculated losses are smaller in value than actually registered ones.

Precisely due to the random nature of some of the causes of energy losses, in our study was used artificial neural networks to predict them. The constructed neural network showed that a continuous gradual reduction of losses in the energy system is expected. Although the rate of loss reduction is also slowing down, relative losses will be about 30% lower in the next few years than in the previous period.

ACKNOWLEDGMENT

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