Secure Systems Design and Technology Development. Veliko Tarnovo, Bulgaria
Proceedings of the International Scientific Conference, 2026. Volume III, 387-391

Analysis of Models for Estimating Electricity Losses in Distribution Networks

Misho Matsankov
Center of competence "Smart mechatronic, eco and energy saving systems and technologies";
Faculty of Electronics and Automation,
Plovdiv branch
Technical University of Sofia
Sofia, Bulgaria
mishel@tu-plovdiv.bg

***Abstract*—The design of renewable energy sources and their connection to the electrical grids at different voltage levels leads to changes in the mode parameters of the grid. Electrical energy losses are of both technical and economic interest. The report examines the most commonly used models for estimating electricity losses in low-voltage distribution networks, depending on the available data under operational conditions. It is proposed to use an improved model with increased accuracy, in the application of which the seasonality coefficient is taken into account.**

Keywords— Electricity losses, electrical networks, low voltage, models.

I. INTRODUCTION

In recent years, the attention paid to ecology has been increasing. Environmental requirements for exhaust gases are increasing, which requires optimization of combustion plants and processes [1, 2]. All of these contribute to the development of renewable sources of electrical energy. The large-capacity renewable sources designed and connected so far were mostly connected to medium and high voltage networks, depending on the specific situation and the network configuration. This led to the depletion of the capacity of some of the power lines. This made low-voltage networks particularly attractive. As a result, increasing number of small-scale solar power plants and zero-consumption buildings are joining into low voltage network [3, 4]. Their production depends not only on meteorological conditions, but also on some other features, such as the cleanliness of their surface [5]. Therefore, monitoring the parameters of the power plants allows optimizing their production [6]. As a result, low-voltage networks undergo rapid operational changes [8-9]. The motivation that owners receive is a combination of the affordable price of the systems, a simplified procedure for obtaining a design and construction permit [10-12]. The creation of energy independence is also not in last place. Despite their local impact, all of them taken together have a significant impact on the operating parameters of the electrical networks. Power losses and, respectively, electrical energy are among the main mode parameters that will be affected. They play a crucial role in the overall efficiency of the electricity grid, affecting operating costs, reliability and resilience of the grid, which is why the accuracy of the models for their assessment is of utmost importance. That is why they represent a constant operational and economic interest. Their share is significant in low-voltage networks, where the currents are high and in some cases the power lines are quite long. Accurate quantification of annual technical energy losses in low-voltage distribution networks is important for grid planning, investment in loss reduction and performance benchmarking. However, an assessment based on high-resolution energy flow time series (e.g., 8760-hour simulation with node/branch level load profiles) is often not possible in practice due to limited metering, uncertain customer load distribution and incomplete feeder data. This has motivated long-term work on methods for estimating annual losses that compress the temporal variability of the load into one or more scalar descriptors (e.g., equivalent loss duration/maximum loss time, load schedule shape descriptors) and/or the spatial complexity of the network into reduced representations with equivalent network diagrams [13, 14]. Large-scale analysis of data from distribution network operators highlights both the significance and heterogeneity of losses in low-voltage networks, with their share in peak load conditions varying across service areas and depending on the network configuration [15]. A large part of the research on the impact of photovoltaic installations on low-voltage networks is that photovoltaic installations can reduce or increase technical losses, depending on the level of penetration, the coincidence with local consumption (self-consumption) and the phase distribution. Detailed studies

Online ISSN 3044-7771
https://doi.org/10.68302/std2026.vol3.150

of the networks report non-monotonic loss behavior, including regimes where losses decrease as photovoltaic installations compensate for local load, and regimes where reverse power flow and voltage increases become significant and can increase losses and operational risks [7-9, 16]. The sensitivity of losses to the location of photovoltaic installations and their penetration depth is reflected in [17]. Analysis methods have begun to address the limitations of observability by reconstructing unmetered consumption and estimating time-varying losses from smart meter data using learned typical load profiles and probabilistic inference [18]. A large number of authors working on low-voltage networks and photovoltaic systems still consider losses primarily as a result of simulation, rather than as a quantity governed by explicitly specified simplified evaluation functions whose parameters (e.g. “equivalent length”, profile-based loss factors, or time scaling) can be calibrated and transferred between supply lines and photovoltaic system deployment scenarios [7, 8, 19, 20]. There is a clear opportunity to more systematically couple the transformation of net load supplied by photovoltaic systems—including self-consumption, power reverse flow periods, and phase distribution—with simplified loss estimation models that remain interpretable, calibratable, and easy to compute, while maintaining fidelity to the mechanisms highlighted by detailed studies of power lines (voltage limitations, unbalance, and power reversal) [7, 8, 16, 21].

Deterministic families of methods such as those based on maximum loss time (equivalent loss duration), “2t” approximations, graphical integration, and average/RMS node loads—have been comparatively reviewed for low voltage industrial or workshop-type networks, with explicit discussion of required input data and typical error sources (e.g., inaccurate estimation of the time of largest losses, ignoring load-shape effects, neglecting conductor heating and contact resistances) [23-25].

A particularly active deterministic thread focuses on the equivalent-duration (maximum-loss time) concept, where annual loss energy is approximated as peak (or reference) loss power multiplied by an “equivalent” number of hours at that level. Recent analysis emphasizes that the empirical relationships used to estimate this duration can exhibit limited validity under strongly uneven or seasonal load schedules, motivating tighter applicability ranges and potentially new empirical models for modern operating conditions [22]. Complementary to these temporal compressions, low voltage -specific work on equivalent resistance in short, equipment-dense shop/industrial networks highlights that non-cable components (e.g., switching-device contact resistances) and temperature-dependent conductor resistance can materially affect loss estimates, and therefore should be included when constructing reduced network equivalents intended for practical calculations [24].

In parallel, a statistically grounded line of research treats loads (and thus currents) as random variables and computes expected I^2 R losses from second-moment information (e.g., mean and variance), rather than explicit time-series simulation. Shenkman’s early formulation of statistical techniques for energy-loss computation provides foundational probabilistic machinery for estimating losses from load statistics [27]. This approach was subsequently specialized toward low voltage distribution networks using variance-based loss computation, directly to capture the quadratic dependence of losses on loading without full temporal detail [26]. Planning-oriented extensions further demonstrate how variance-based estimators can support distribution-network studies when only partial data are available [30].

Between these deterministic and probabilistic poles, several “simplified” or hybrid feeder-level models combine feeder characteristics (e.g., length, peak demand) with load profile descriptors (e.g., load factor or statistical moments of daily load curves), aiming to operate across different regimes of data availability [28, 29]. Collectively, this literature suggests a spectrum of annual-loss estimation methodologies with distinct assumptions about load synchrony, spatial load distribution stability, and the availability/quality of schedule statistics. At the same time, the retrieved works do not appear to provide a single, unified head-to-head comparison of all classical approximation families on common low voltage feeders, implying that integrated benchmarking against detailed load-flow remains an open and practically relevant research task [22-25, 28-30].

The most commonly used methods for estimating electrical energy losses in low-voltage distribution networks are examined, depending on the information provided. It is proposed to take into account the seasonality coefficient, which would increase the accuracy of the models. Depending on the operating conditions, the network configuration and its declared voltage, different methods are applied to calculate the network operating parameters, such as voltage levels in the nodes, power losses and electrical energy.

II. Materials and Methods

The study examines a branch of a low-voltage electrical network from a small settlement with large section lengths and low density of electrical loads. The diagram in Fig. 1 shows the section lengths and powers in maximum load mode without taking into account the impact of installed renewable sources.

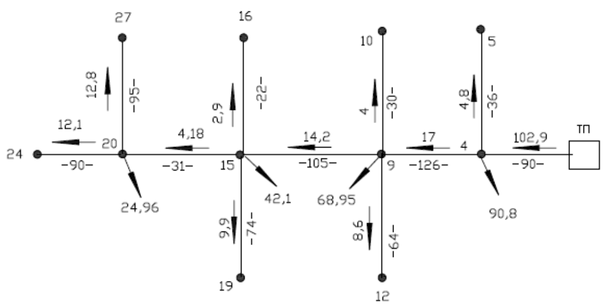

Fig. 1. electrical diagram of a low voltage distribution network

All consumers have installed photovoltaic systems that meet the latest requirements described in [10] and [11].

Methods for calculating the modes of electrical networks, voltage levels in nodes, power and energy losses are applied depending on the declared voltage, network configuration and operating conditions [31-33]. Models for calculating technical losses of electricity in low-voltage electrical networks require different available information. The most commonly used models for determining electricity losses in low voltage electrical networks are presented below:

A. Model with the equivalent length of the power line and the filling factor k, of the load profile

Electricity losses in low-voltage electrical networks based on operational data are determined by the (1) from [21, 24]:

$$\Delta W = k_H \frac{W^2.(1+tg^2\varphi).L_e}{s.T}.\frac{1+2.k_3}{3.k_3} \quad (1)$$

Where:

W is the electricity delivered to consumers for a specified period;

T is consumption period (expressed in days);

s is the cross-section of the conductor in the main line;

L_e is the length of the power line;

tg 4 is the reactive power factor;

K_n - the coefficient taking into account the nature of the distribution of loads along the length of the power line and the inequality of the loads of the phases.

The equivalent length of the line is determined by (2).

$$L_e = L_M + k_{2-3}.L_{2-3} + k_1.L_1 \quad (2)$$

Where:

L_M is the length of the highway;

L_{2-3} is the length of two-phase and three-phase deviations and the corresponding coefficient is K_{2-3}=0,44;

L_1 is the length of single-phase deviations and the corresponding coefficient is K_1 = 0,22;

The coefficient Kn is determined by (3).

$$k_H = 9{,}67 - 3{,}32d_p - 1{,}84d_p^2 \quad (3)$$

Where d_p is that part of the energy that is used in the domestic sector

When using (1) to determine the losses in N lines with a total length of the mains L_{Msum}, two-phase and three-phase deviations $L_{2\text{-}3sum}$ and single-phase deviations L_{1sum}, the average released electricity in one line W = Ws / N is taken, where W_{sum} is the total released energy in N lines.The coefficient K_n, determined by (3), is multiplied by the coefficient K_N, which takes into account the inequality of the lengths of the lines and the current densities in the mains.

$$k_N = 1{,}25 - 0{,}14d_p \quad (4)$$

When there is no data on the load schedule filling factor and the reactive power coefficient, k_3, = 0.3; tg φ = 0.6 is assumed.

B. Model using the total length Lsum and the fictitious duration t of power losses

$$\Delta W = \Delta P_c.L_\Sigma.\tau \quad (5)$$

Where ΔP is the average value of power losses per 1 km of the power line at maximum load.

$$\Delta P_c = 3.\left(\frac{S_H.k_{HT}}{\sqrt{3}.U}.k_p\right)^2.r \quad (6)$$

Where:

S_n is the nominal power of the power transformer;

K_{nt} is the average load of the transformer at maximum load;

K_p is the load distribution coefficient along the length of the line;

d is the active resistance per 1 km of the conductor.

C. Model with determination of voltage losses to the electrically farthest node from the transformer substation

This approach allows to determine the power losses through the voltage losses to the electrically most remote node from the transformer station, taking into account the unevenness of the load of the phases in the low-voltage network. The results of the measurements of the voltage levels in the transformer station and at the electrically most remote point of the network, the phase currents IA, Ib. Is of the main line during the maximum load are used as the initial information.

$$\Delta W_{\%} = K_{mn}.K_{al}.\Delta U_{cr\%}.\tau \quad (7)$$

Where:

$U_{av\%}$ is the average value of voltage losses.

K_{al} is the coefficient of additional losses, which takes into account the unevenness of the phase load.

$$k_{al} = 3.\frac{I_A^2 + I_B^2 + I_C^2}{(I_A + I_B + I_C)^2}.\left(1 + 1{,}5\frac{R_H}{R_\Phi}\right) - 1{,}5.\frac{R_H}{R_\Phi} \quad (8)$$

Where:

R_H and Rф are the resistances of the neutral and phase conductors.

K_{to} - the coefficient which depends on the network configuration and load density.

$$K_{mn} = \frac{K_b.2r}{\left(2.r.\cos^2 \varphi + x.\sin 2\varphi\right)} \quad (9)$$

Where:

r and x are the active and reactive resistance of the highway;

K_b - the branching coefficient of the circuit [31, 34].

D. A probabilistic approach with a known maximum load Pmax and a specified type of load schedule.

The coefficient кр is determined depending on the available data [31, 34].:

the mathematical expectation of the maximum load P_T according to the typical load schedule is determined by (10):

$$k_p = \frac{\sqrt{\left(\frac{\beta.V.\overline{P_T}}{200}\right)^2 + \overline{P_T}.P_{\max}} - \frac{\beta.V.\overline{P_T}}{200}}{\overline{P_T}} \quad (10)$$

Where:

β - the confidence coefficient (β в =2 at a confidence probability of 0.975);

B_p - the coefficient of variation of the maximum load.

When the value of the mathematical expectation of the maximum active power P_{max} is known:

$$k_p = \sqrt{\frac{\overline{P}_{\max}}{\overline{P}_T}} \quad (11)$$

When the amount of electricity consumed W per year is known:

$$k_p = \sqrt{\frac{W}{W_T}} \quad (12)$$

The annual electricity consumption W corresponding to the given load schedule is determined by (13).

$$W_T = \frac{\sum_{k=1}^{12} m_k.\overline{P}_{CT}.\sum_{j=1}^{12} k_{pj}.\sum_{i=1}^{24} P_{ik}}{1200} \quad (13)$$

where $к_{pj}$ is the seasonality coefficient;

Ric is the mathematical expectation of the active power in the i_{th} hour of the k_{th} season, where t is the number of days in the month.

III. Results and Discussion

The results of the calculations performed using the compiled algorithms of the four models are summarized in Fig. 2. The errors made in determining electricity losses depending on the load schedule fill factor when applying the following models are shown:

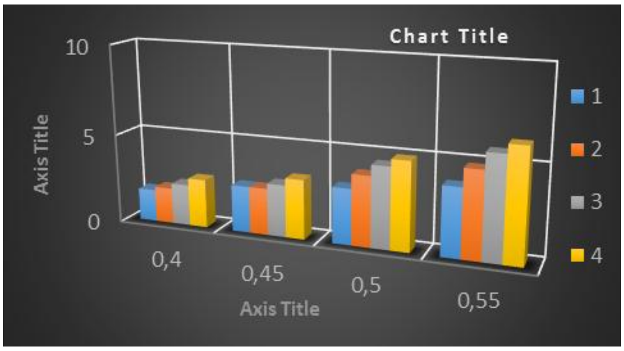

Fig. 2. distribution of errors in determining losses depending on the load schedule fill factor

1 - using the equivalent length of the power line and the load schedule filling factor;

2 - with the total length of the power lines and the fictitious duration:

3 - with determination of the voltage losses to the electrically farthest node from the transformer station;

4 - with a probabilistic approach with a known maximum load Pmax and a given typical load schedule.

The error is calculated relative to the basic method for approximation discretization of the known load schedule with a step shape at a very high degree of discretization.

Fig 2. Errors in determining electricity losses depending on the load schedule fill factor when applying models 1+4 for a low voltage distribution network. It is established that the error is the largest when applying the second model, and the smallest when applying the fourth model.

As the load schedule fill factor increases, the allowable calculation error increases.

IV. Conclusions

- The model using the equivalent length of the power line and the load schedule fill factor is recommended in the absence of measurements and the availability of data on energy consumption in the residential sector.
- The most inaccurate model is the one using the total length Lsum and the fictitious duration τ due to its approximate selection.
- A model with determination of voltage losses to the electrically most remote node from the substation, using control measurements of voltages in the supply node and phase currents in the highway during maximum load, is more accurate than the first model. The approach is relatively easy to implement, but it is difficult to determine the coefficient Kmp.
- The first three models can be considered as evaluative in the case of an insufficiently developed information system for calculating modes and losses in low voltage networks.
- The fourth model is the most accurate and promising. It can be used without problems in modern technical

equipment and the coordination of the work of distribution networks and regional dispatching services.

V. Acknowledgments

The authors would like to express their gratitude to the management of the project No. BG16RFPR002-1.014-0005 Competence Center "Intelligent Mechatronics, Eco- and Energy-Saving Systems and Technologies" for their financial support.

References

[1] A. N. Sapargaliyeva, A. M. Dostiyarov, D. Umyshev, A. K. Baidalina, A. S. Begimbetova, N. N. Sarakeshova and Z. F. Ozhikenova, " Experimental Investigation of an Air-Staged Swirl Burner with Hemispherical Stabilizer for Low-NO_x Combustion", MDPI February 2026 19 (4), DOI:10.3390/en19040897.

[2] A. M. Dostiyarov, A. N. Sapargaliyeva, A. K. Yamanbekova and I. K. Iliev, "Development of a new front heat generator device and results of numerical simulation on Comsole Multiphysics", 9th International Conference on Energy Efficiency and Agricultural Engineering 2024, DOI:10.1109/EEAE60309.2024.10600586.

[3] K. Seymenliyski, A. Yovkov, E. Zaerov, V. Todorov, R. Simionov and H. Mihaylov, "Modern Technological Solutions for Passive Buildings and Buildings with Zero Energy Consumption", Telecommunications and Remote Sensing juli 2025 (pp.87-99), DOI:10.1007/978-3-031-99332-9.

[4] N. Mihaylov, B. Evstatiev, S. Kadirova, T. Gueorguiev, T. Georgieva and A. Evtimov, "Load Profile of Typical Residential Buildings in Bulgaria", IOP Conference Series: Earth and Environmental Science 2018, DOI: 10.1088/1755-1315/172/1/012035.

[5] M. Vassilev, B. Stankov, P. Zlateva, and M Karimoldanova, "Influence of Thermophoresis on the Deposition of Limestone Dust Particles on Solar Panel Surfaces"

[6] A. Chekichev, A. Parushev, R. Popov, N. Paunkov, M. Bundeva, Microprocessor System for Studying the Operating Characteristics of the Photovoltaic Panels, TELECOM 2024, DOI: 10.1109/TELECOM63374.2024.10812301

[7] G. Fernández, N. Galan, D. Marquina, D. Martínez, A. Sanchez, P. López, H. Bludszuweit and J. Rueda. "Photovoltaic Generation Impact Analysis in Low Voltage Distribution Grids", Energies 2020, 13(17), DOI: 10.3390/en13174347

[8] J. Bendík, M. Cenký, B. Cintula, A. Beláň, Ž. Eleschová and P. Janiga. "Stochastic Approach for Increasing the PV Hosting Capacity of a Low-Voltage Distribution Network". DOI: 10.3390/pr11010009.

[9] Y. Gabdullin and B. Azzopardi, "Impacts of Photovoltaics in Low-Voltage Distribution Networks", Energies 2022, 15(18), 6731; DOI:10.3390/en15186731.

[10] Law on Territorial Planning, Last amended 17 Oct 2025.

[11] Renewable Energy Sources Act. Last amended on Nov 14, 2025.

[12] Standard BDS EN 50160, Last amended 2023.

[13] E. Yu. Gracheva, Z. M. Shakurova and R. E. Abdullazyanov, "A comparative analysis of the most common deterministic methods for the calculation of electricity losses in industrial networks", Power engineering: research, equipment, technology, 2019, 21(5):87-96, DOI:10.30724//1998-9903-2019-21-5-87-96.

[14] E. Gracheva and A. Alimova, "Calculation Methods and Comparative Analysis of Losses of Active and Electric Energy in Low Voltage Devices", International Ural Conference on Electrical Power Engineering 2019, DOI:10.1109/URALCON.2019.8877627

[15] M. Kornatka and A. Gawlak. "An Analysis of the Operation of Distribution Networks Using Kernel Density Estimators", Energies 2021, 14(21), 6984; DOI:10.3390/en14216984.

[16] I. C. Torres, G. F. Negreiros and C. Tiba. "Theoretical and Experimental Study to Determine Voltage Violation, Reverse Electric Current and Losses in Prosumers Connected to Low-Voltage Power Grid". Energies 2019, 12 (23), 4568; DOI:10.3390/en12234568.

[17] A. Gawlak and M. Kornatka, "Analysis of the Impact of Photovoltaic Generation on the Level of Energy Losses in a Low-Voltage Network". Energies 2024, 17 (23), 5957, DOI:10.3390/en17235957.

[18] R. Telford, R., B. Stephen, J. Browell and S. Haben. "Dirichlet Sampled Capacity and Loss Estimation for LV Distribution Networks With Partial Observability", IEEE Transactions on Power Delivery, DOI:10.1109/TPWRD.2020.3025125

[19] M. T. Au and C. H. Tan. "Energy flow models for the estimation of technical losses in distribution network". IOP Conference Series: Earth and Environmental Science 16(1):2035, DOI:10.1088/1755-1315/16/1/012035

[20] M. Verdelho, R. Prata, P. Carvalho and J. Machado. "Impact of PV distributed generation on EDP distribuição LV grid losses". CIRED - Open Access Proceedings Journal 2017 (1):2342-2345, DOI:10.1049/oap-cired.2017.0306.

[21] O. Ivanov, B. Neagu, A Cibotărică and M Gavrilaş. "Multiobjective Prosumer Surplus Management for Optimal Microgrid Operation". 10th International Conference on ENERGY and ENVIRONMENT 2021.

[22] V. Bodunov, G. Oleksandr, T. Kulko and A. Prystupa, "Estimation of Existing Models of the Maximum Duration of Active Energy Losses in Distribution Networks", Bulletin of the National Technical University «KhPI» Series: New solutions in modern technologies, 2023, DOI:10.20998/2413-4295.2023.02.01

[23] E. Gracheva, Z. Shakurova and R. Abdullazyanov, "A comparative analysis of the most common deterministic methods for the calculation of electricity losses in industrial networks " Power engineering: research, equipment, technology, 2019 21(5):87-96. DOI:10.30724//1998-9903-2019-21-5-87-96

[24] E. Gracheva and A. Alimova, "Calculation Methods and Comparative Analysis of Losses of Active and Electric Energy in Low Voltage Devices", 2019 International Ural Conference on Electrical Power Engineering (UralCon), 2019.

[25] E. Gracheva, A. Alimova, "Сравнительный анализ и исследование методов расчета потерь электроэнергии в системах электроснабжения промышленных предприятий", 2018.

[26] O. M. Mikic, "Variance-Based Energy Loss Computation in Low Voltage Distribution Networks", IEEE Transactions on Power Systems, 2007

[27] A. Shenkman, "Energy loss computation by using statistical techniques", IEEE Transactions on Power Delivery, 1990

[28] M. T. Au and C. H. Tan, "Energy flow models for the estimation of technical losses in distribution network", IOP Conference Series: Earth and Environmental Science, 2013

[29] T. M. Anthony, M. Yusoff, "A simplified approach in estimating technical losses in distribution network based on load profile and feeder characteristics", 2008 IEEE 2nd International Power and Energy Conference, 2008

[30] J. Dickert, M. Hable and P. Schegner, "Energy loss estimation in distribution networks for planning purposes", 2009 IEEE Bucharest PowerTech, 2009, DOI:10.1109/PTC.2009.5281997

[31] P. Notov and St., Nedeltcheva, Electroenergetics, Volume 1, TU – Sofia Publishing house, Sofia, 2009.

[32] P. Notov and St., Nedeltcheva, Electroenergetics, Volume 2, TU – Sofia Publishing house, Sofia, 2009.

[33] St. Nedeltcheva, Electrical networks and systems with decentralized generating sources, ISBN 978-619-167-348-3, TU – Sofia Publishing house, Sofia, April 2018.

[34] Nedelcheva S., Application of mathematical models for determining the losses of electricity in CH and HV power lines. Anniversary scientific conference, Sliven'97.