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RESEARCH ARTICLE

Monthly Probability Theoretical Line Loss Calculation Method of Low Voltage Distribution Network Based on Simultaneous Power and Electricity

YUNZHAO FENG, LIANGYU LONG, AND JIAYUE QIAN
College of Electrical Engineering and Renewable Energy, China Three Gorges University, Yichang, Hubei 443002, China

Corresponding author: Yunzhao Feng (miliisiriel92a@gmail.com)

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ABSTRACT The probability analysis method of theoretical line loss (TLL) is an emerging TLL assessment method in recent years, which can consider the impact of random changes in load, power source, and other factors on the line loss rate, and can accurately evaluate the distribution range of line loss rates in a specific power grid in the long, medium, and short term. A monthly probability theoretical line loss calculation method of low-voltage network (LVN) based on simultaneous power and electricity is proposed in this paper. This method firstly converts hourly calculations of line loss into every 20 minutes calculations, which can shorten the calculation interval based on the first power, last power, and electricity collected in every hour by the user's smart meter. Then, based on improved K-means clustering method (KCM) and non-parametric Kernel density estimation, the load probability distribution model is established, and the acceptance-rejection sampling method (ARSM) is used to generate the power random samples of each user's load for every 20 minutes in a month. The three phase power flow of each simulation sample is calculated by using the injection Newton's method. Then, the monthly TLL is accumulated. Finally, based on the IEEE-13 buses and IEEE-33 buses standard distribution system, the simulation results showed that the proposed method can more accurately and effectively calculate the monthly probability TLL of LVN compared with the line loss calculation method based on daily and hourly electricity.

INDEX TERMS Smart meter, low voltage network, power flow calculation, TLL.

I. INTRODUCTION

For energy conservation and emission reduction, improving the level of management and operational efficiency of enterprises, and responding to the impact and challenges of the new electricity reform, energy enterprises have clearly studied the goal of power grid loss reduction and continue to promote it as an annual key work [1]. The line loss analysis of power grid in the LVN is an important component of line loss management in power system, and it is also the most important way to promote the scientific and reasonable construction, transformation and operation in the LVN [2].Therefore, in terms of how to efficiently calculate the line loss rate in the LVN, it is crucial to study a reasonable TLL calculation method [3].

Since the beginning of the 1920s to 1930s, researchers have been engaged in research on TLL calculation in distribution networks, studying the mechanism of energy loss generated by various power components, analyzing the reasons for power loss in network transmission, and constructing mathematical models to calculate the TLL of the network [4], [5]. Among all levels of power grids, the line loss of LVN is the most severe, which is one of the important reasons for the overall high line loss rate in the power grid. The potential for

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reducing losses in LVN is enormous, and it is an important part of online loss management and reduction work for power grid enterprises [6].

The line loss includes two parts: TLL and management line loss [7]. The TLL mainly depends on the network parameters, and is the theoretical electricity consumption value of each component during real-time operation [8]. The main sources of management line losses are inconsistent meters (smart meters do not match with the belonging network), metering faults, and electricity theft [9]. Therefore, strengthening management measures can reduce or even avoid the causes of line losses mentioned above [10]. Seen from this, the key to reducing line loss lies in defining the boundary between TLL and management line loss, clarifying the space for reducing line loss, and providing theoretical basis and scientific support for formulating line loss reduction measures [11].

Literature [12] analyzed the composition, distribution and influencing factors of line loss in the main network of a provincial power grid by using the measured results of load, and analyzed the influence of wind power integration on line loss. In literature [13], a three-phase imbalance factor is introduced into the calculation of branch line loss, and the forward-backward method is modified to calculate theoretical line loss. Compared with the equivalent resistance method, the improved algorithm has higher accuracy and applicability, which is helpful to further develop the theoretical line loss calculation task in the LVN.

At present, there are some bottlenecks of line loss management in the LVN: (1) The traditional theoretical line loss calculation in the LVN needs high-precision power grid structure and network parameters, due to insufficient data and poor reliability, comprehensive and in-depth research of line loss calculation in the LVN has not been carried out. (2) The line loss target is set in the same way in the different LVN, without fully considering the actual operating conditions, such as the load characteristics of different users and the influence of distributed generation. (3) Topological structure and network parameters are the basis for accurate calculation of line loss, however, these data are still obtained manually. Nowadays, with the continuous promotion and development of the construction of intelligent distribution networks, smart meters have been basically promoted and applied in the LVN. Smart meters have three-phase power flow and electricity data, which lays a necessary data foundation for the TLL calculation in the LVN [14], [15], [16].

The probability analysis method of TLL is an emerging method for evaluating TLL in recent years [17]. This method can consider the impact of random changes in load, power source, and other factors on line loss rate, thus can accurately evaluating the distribution range of line loss rate in a specific power grid in the long, medium, and short term [18]. Moreover, probability analysis methods do not entirely rely on measured information and actual network structure information, simulation methods can be used to obtain system state and even network structure parameters, avoiding the collection of a large amount of data, thereby greatly improving the efficiency of line loss rate calculation [19], [20], [21].

Therefore, a monthly probability theoretical line loss calculation method of LVN based on simultaneous power and electricity is proposed in this paper. The main contributions in this paper are as follow:

(1) By using first power, last power, and electricity collected in every hour, daily and hourly calculation of line loss is converted into 20 minutes calculation, which can shorten the calculation interval and improve the accuracy of TLL calculation.

(2) By using the improved KCM and non-parametric Kernel density estimation, the load probability distribution model is established, and the ARSM is used to generate the power random samples of each user's load. Monthly probability theoretical line loss can help clarifying the space for reducing line loss, and providing theoretical basis and scientific support for formulating line loss reduction measures with out entirely rely on measured information and actual network structure information.

II. HOURLY LEVEL SIMULTANEOUS POWER AND QUANTITY MEASUREMENT

In the LVN, the low voltage side of the distribution transformer's main smart meter and user's sub smart meter can intelligently collect measurements such as three-phase electricity W_{hour}, active power P_{hour}, reactive power Q_{hour}, power factor $\cos\varphi_{hour}$ etc [20]. The schematic diagram of power and electricity measurements collected by smart meter in an hour is shown in Figure 1.

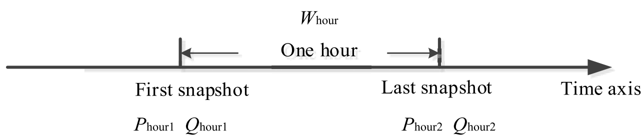

FIGURE 1. The schematic diagram of power and electricity measurements collected by smart meter in an hour.

Where P_{hour1}, Q_{hour1} represent the first active and reactive power of first snapshot in an hour; P_{hour2}, Q_{hour2} represent the last active and reactive power of last snapshot in an hour; W_{hour} represents the electricity consumed in an hour.

During the hour level time period, the average active power $\bar{P}_{hour}$ can be obtained based on the electricity measurement W_{hour}:

$$\bar{P}_{hour} = W_{hour} \tag{1}$$

The average reactive power $\bar{Q}_{hour}$ can be obtained based on the power factor $\cos\varphi_{hour}$ and average active power $\bar{P}_{hour}$:

$$\bar{Q}_{hour} = \bar{P}_{hour} \times \tan\varphi_{hour} \tag{2}$$

Therefore, the power measurements collected in an hour include the first power data P_{hour1}, Q_{hour1}, the last power data P_{hour2}, Q_{hour2} and the average power data. Seen from this, there are three power values in each hour level time period. In this paper, we assume that each power value accounts for one third of the duration, that is, 20 minutes.

The measurement data used in this paper is compared with the previous works, i.e. the line loss calculation method using daily electricity [17] (called method 1 in this paper) and the line loss calculation method using hourly electricity [18] (called method 2 in this paper), as shown in Table 1.

TABLE 1. The comparison of data used in different methods.

Data used	Method 1	Method 2	The proposed method
Time interval	1 day	1 hour	20 minutes
Power data	/	/	The first and last power in an hour
Electricity	Daily electricity	Hourly electricity	Hourly electricity

By using the power and electricity data in the hour level time period, the time interval of theory line loss calculation is shortened compared with the previous line loss calculation method based on daily electricity and hourly electricity, thus can improve the accuracy of TLL calculation.

III. LOAD RANDOM SIMULATION METHOD FOR LVN BASED ON KCM

A. IMPROVED K-MEANS CLUSTERING METHOD

The algorithm of KCM [22] is a classic unsupervised clustering algorithm. Its basic idea is: for a set containing N data, randomly select k objects as the starting clustering center and calculate the Euclidean distance (ED) between N data and k centers. Then, the N data is divided into k clusters with the smallest distance from the clustering center. After all data is allocated, the clustering centers of each cluster are calculated again and repeat the above clustering division until the cluster center remains constant.

The degree of similarity (or difference) between data objects is generally calculated using a mathematical function. KCM usually uses ED to measure the similarity of data objects, and the ED between array $X(x_1, x_2, \cdots, x_n)$ and array $Y(y_1, y_2, \cdots, y_n)$ is:

$$d(X, Y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \cdots + (x_n - y_n)^2} \tag{3}$$

where $d(X, Y)$ represents the ED between the array $X(x_1, x_2, \cdots, x_n)$ and the array $Y(y_1, y_2, \cdots, y_n)$.

At the same time, KCM uses the sum of error's square as the standard to judge whether the clustering is over. The definition of the sum of error's square e is:

$$e = \sum_{i=1}^{k} \sum_{x_j \in C_j} (x_j - c_j)^2 \tag{4}$$

where c_j represents cluster center in the j-th cluster; C_j represents the j-th cluster. From the formula (4), it can be seen that the sum of error's square e reflects the closeness between each cluster data and the cluster center. The smaller the value, the closer the cluster obtained by clustering.

The implementation steps of KCM can be described as follows:

(1) Input the data set S and the number of clusters k.

(2) Select randomly k data from data set S as the starting clustering center.

(3) According to the ED calculation formula, calculate the ED between the data of data set S and each starting cluster center, and divide the data of S into closest clusters based on the ED value.

(4) Recalculate the centers of k clusters.

(5) Calculate the value of the sum of error's square, and if it converges, the algorithm ends and the result is output. On the contrary, return to step (3) until e reaches the convergence condition.

K-means clustering algorithm has simple steps and is easy to implement, and which also can be directly called in the MATLAB library functions. However, KCM must set the value of clustering number in advance, and the appropriate value k is very important for the final clustering result. Therefore, the improved KCM is used in this paper [23].

Suppose that the data set S is clustered into k clusters, $C = \{C_1, C_2, \cdots, C_k\}$ represents all the cluster sets, and n_i represents the number of data in the cluster C_i. In this paper, the following indicators are used to evaluate the clustering results (called CH index):

$$CH = \frac{traceB}{k-1} \Big/ \frac{traceW}{N-k} \tag{5}$$

$$traceB = \sum_{i=1}^{k} n_i (d(z_i, z))^2 \tag{6}$$

$$traceW = \sum_{i=1}^{k} \sum_{j=1}^{n_i} (d(x_j, z_j))^2, x_j \in C_j \tag{7}$$

where CH represents the indicators of evaluating the clustering results; z represents the average value of the data set S; z_j represents the average value of the j-th cluster C_j. The smaller the CH, the better the clustering result.

The implementation steps of calculating the optimal cluster number k in improved KCM are as follows:

(1) Determine the search range of cluster number $[k_{\min}, k_{\max}]$, and increase the number of clusters k from $k_{\min}$ to $k_{\max}$ in turn.

(2) Obtain the clustering results based on the steps of KCM.

(3) Calculate the CH index of the clustering results under different clustering numbers

(4) Determine the best clustering number and output the corresponding clustering results.

B. NON-PARAMETRIC KERNEL DENSITY ESTIMATION

The user's load in the LVN is called the disturbance quantity, which fluctuates randomly and is a random disturbance variable with strong uncertainty. Therefore, it is necessary to accurately simulate the random fluctuation characteristics of load changes.

To describe the random fluctuation characteristics of loads, the current researches generally are as follows: firstly, assume that the load follows a certain assumed distribution; then, estimate the parameters of the assumed distribution based on historical data; finally, obtain the probability distribution model of the load. However, the main problem of this modeling approach is that they assume the user's load follows a given distribution, which rely on subjective experience and lack of theoretical basis. The random characteristics of the actual load itself may have a significant difference from the assumed distribution.

For this reason, this paper use Kernel density estimation in load probability modeling, which is a method that does not need any prior knowledge, make any assumptions, and study data distribution characteristics from data samples, with high simulation accuracy and strong adaptability [24].

Suppose $p_1, p_2, \ldots, p_n$ are n data samples of load p, and the probability density function of p is $f(p)$, then the Kernel density estimation $f_h(p)$ corresponding to $f(p)$ is:

$$f_h(p) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{p-p_i}{h}\right) \tag{8}$$

where: p represents variable; h represents the bandwidth; n represents the number of samples; $K()$ represents kernel function.

The selection of kernel function $K()$ is often chosen as a probability density function centered around 0 with the following characteristics:

$$\begin{cases} \int K(u)du = 1 \\ \int uK(u)du = 0 \\ \int u^2K(u)du = \sigma > 0 \end{cases} \tag{9}$$

where: u represents variable; σ represents the variance of u.

Gaussian function, also known as standard Normal distribution function, meets all requirements of Kernel density estimation theory for kernel function, and is widely used in mathematical theoretical analysis and practical application. Therefore, this paper also uses Gauss kernel function to carry out probability modeling of load.

C. ACCEPTANCE-REJECTION SAMPLING METHOD

In probability analysis of loads, firstly, generate random samples through sampling, and then proceed with the next step of simulation analysis. This paper introduces the ARSM to obtain random samples of loads. Assuming the bus load is x, the probability density function is $f(x)$, the maximum value is M, the value domain of x is $[a, b]$, and the random sample is e, the specific steps are as follows [25]:

(1) In interval [0, 1], generate random numbers r and r_i that satisfy a uniform distribution;

(2) Calculate e based on the value r and $[a, b]$;

(3) If $r \leq f(e)/M$, accept sample e, otherwise return to step (1) to continue sampling.

The specific operation process of the ARSM is shown in Figure 2.

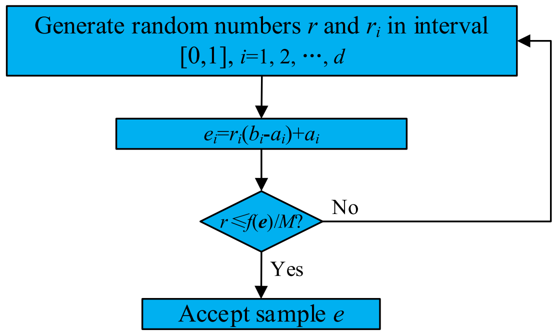

FIGURE 2. The specific operation process of the ARSM.

D. RANDOM SIMULATION METHOD FOR POWER LOAD IN LVN

Based on the user's smart meter measurement, power data collected at the first and last snapshot of each hour and the hourly electricity consumption can be obtained.

The logic diagram of random simulation method for power load is shown in Figure 3.

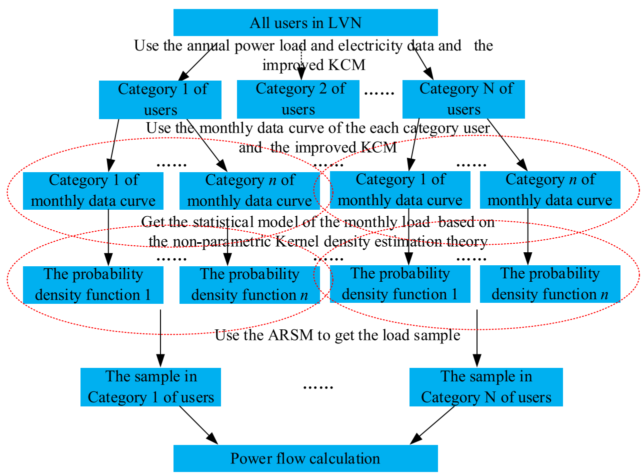

FIGURE 3. The logic diagram of random simulation method for power load.

The specific steps of random simulation method for power load are as follows:

(1) By organizing annual power load and electricity data of users in LVN (i.e. 8760 hours), and using the improved KCM, the users' load can be divided into N categories;

(2) For each category of power load, the monthly data curve of the user's load can be clustered using the improved KCM. The monthly data curve of the user's load can be divided into n categories, and the mean curve of the monthly data of each category can be used as the typical monthly load data curve.

The number of samples contained in each category is used as the frequency of the corresponding typical month, and the typical monthly load curve is considered random and follows a uniform distribution;

(3) For the typical monthly load curve of each category, the statistical model of the monthly load of is established based on the non-parametric Kernel density estimation theory;

(4) Generate a random number x in the interval [0, 1], determine the typical monthly curve of each category according to x, use the ARSM to get the load sample, and obtain power flow data of each hour for each month.

IV. MONTHLY PROBABILITY TLL CALCULATION

A. INJECTION NEWTON'S METHOD FOR POWER FLOW CALCULATION

For the power flow data obtained by random sampling, which is calculated by using the injection Newton's method. In the LVN, for any bus, the injection current expression is as follow [26]:

$$I_i = \sum_{j=1}^{N} Y_{ij} U_j \tag{10}$$

where: I_i represents the injection current at bus i; Y_{ij} represents the mutual admittance between bus i and bus j; U_j represents the voltage at bus j; N represents the total number of buses.

Based on the injection Newton's method, establish the power flow equations. After Taylor expansion and linearization, the correction equation can be obtained as follows:

$$[\Delta j, \cdots, \Delta v]^T = H\left[\Delta x_j, \cdots, \Delta x_v\right]^T \tag{11}$$

where: Δj and Δv represent the unbalance quantities of PQ and PV bus, respectively; H represents the Jacobi matrix; Δx_j and Δx_v represent the correction quantities of state variables for PQ and PV bus, respectively.

At the k-th iteration, the increment of the state variable is:

$$x^{(k+1)} = x^{(k)} + \Delta x^{(k)} \tag{12}$$

where: $x^{(k)}$ and $x^{(k+1)}$ represent the state variables at the k-th and $(k+1)$-th iteration, respectively; $\Delta x^{(k)}$ represent the increment of $x^{(k)}$ at the k-th iteration.

The flow chart of power flow calculation for injection Newton's method is shown in Figure 4.

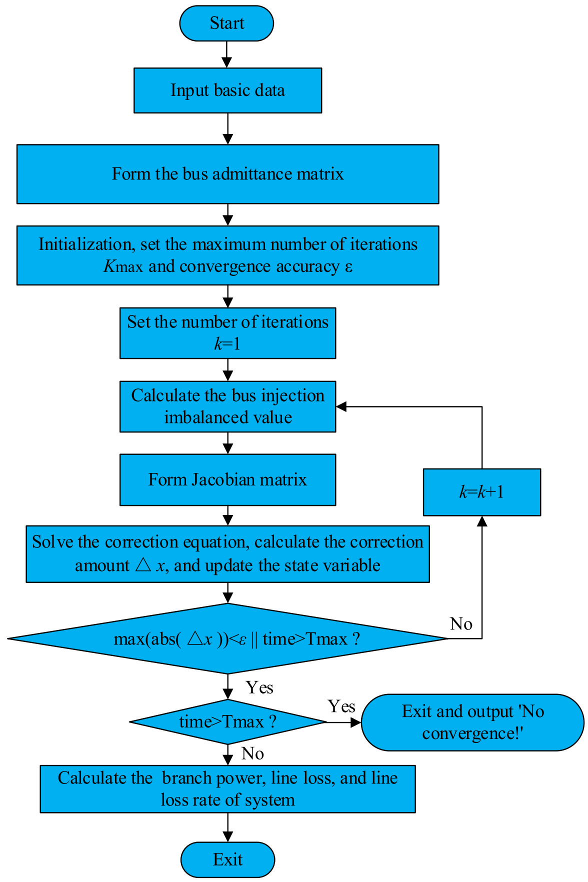

FIGURE 4. The flow chart of power flow calculation for injection Newton's method.

B. MONTHLY PROBABILITY TLL CALCULATION STEPS

Based on Monte Carlo simulation method, the probability distribution of monthly TLL in the LVN is calculated (assuming 30 days per month, 3 power data points per hour, therefore, there are a total of 2160 power data points in a month).

The specific calculation steps are as follows:

(1) Initialization: input historical measured data and network structure parameters of LVN, set sampling samples $k_{\max}$, convergence threshold ε, and set the initial number of samples $k = 0$;

(2) Power load state simulation: based on the KCM and non-parametric Kernel density estimation, a statistical model of each bus load is established, and three random power samples of each user's load in each hour for a month are generated by using the ARSM;

(3) Simulation of power flow state: calculate power flow based on injection Newton's method by using random load samples and network structure parameters at each power data point, and obtain monthly TLL samples;

(4) Convergence judgment: calculate the variance of all monthly TLL sample data η. If $\eta \leq \varepsilon$ or $k \geq k_{\max}$, the sampling will be stopped, and the results will be output. Count the calculated monthly TLL samples, and their histograms or probability density curves will be plotted. Otherwise, $k = k+1$, go back to step (2).

The flowchart of monthly probability TLL calculation method is shown in Figure 5.

V. NUMERICAL TEST AND ANALYSIS

A. BASIC DATA

Based on the IEEE-13 buses standard distribution system, an improved IEEE-13 buses system is established. The improved system topology is shown in Figure 6. In this distribution network, the total load is 3107.43kW + j1831.83kVar.

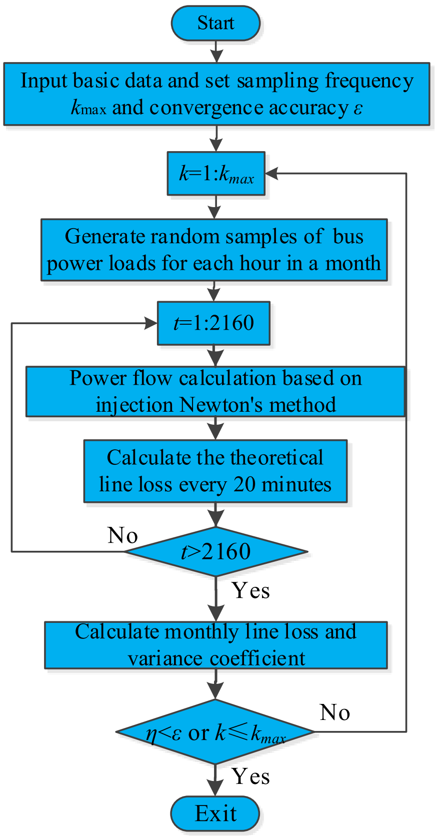

FIGURE 5. The flowchart of monthly probability TLL calculation method.

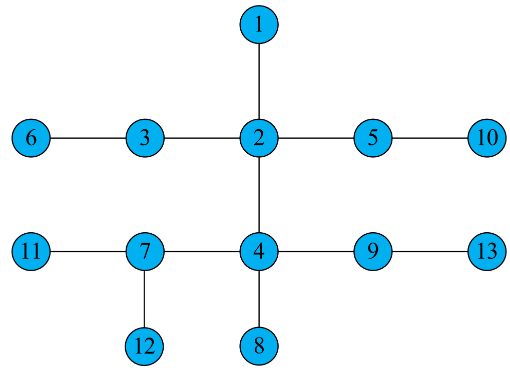

FIGURE 6. IEEE-13 buses distribution system structure connection diagram.

TABLE 2. Monthly TLL calculated by three cases (kWh).

results	calculated value		
Method	Method 1	Method 2	The proposed method
TLL	139.74	131.76	127.46
TLL rate	2.60%	2.45%	2.37%
synchronous line loss	124.72	124.72	124.72
synchronous line loss rate	2.32%	2.32%	2.32%
line loss difference	15.02	7.04	2.74
percentage error	12.07%	5.60%	2.16%

The construction process of the improved system is as follows: (1) All branch are set as 501, and the phase spacing is 1.1292m; (2) The resistance of phases A and B of lines 7-11 is 0; (3) The load is constant power; (4) Ignore parallel capacitors, voltage regulators, and distribution transformers. Bus 5, 7, and 8 are zero injection bus, bus 1 is set as balanced bus.

B. SIMULATION RESULTS AND ANALYSIS

(1) Monthly deterministic TLL calculation and analysis

Based on the improved IEEE-13 buses system, the line voltage was modified to 380V to simulate the actual voltage of the LVN. The monthly deterministic TLL calculation is carried by using the monthly electricity and power data from the low-voltage side of the distribution transformer in an actual standard LVN. In order to prove the effectiveness of the method proposed in this paper, the previous works, i.e. the line loss calculation method using daily electricity [17] (called method 1 in this paper) and the line loss calculation method using hourly electricity [18] (called method 2 in this paper) are compared in the simulation.

Method 1 [17]: Monthly TLL calculation based on daily electricity

This method is a calculation method for actual existing distribution systems, which uses the total daily electricity data of the LVN, divides it by 24 hours to obtain the average value of the daily power, and uses it in injection Newton's method for power flow calculation to obtain the TLL in a day.

The details of the operation are as follows: firstly, the daily electricity data is divided by 24 hours to obtain the average value of the daily power, which is used as the total three-phase active power of the day in the LVN. Based on the power factor, assuming the given power factor is 0.9, the total reactive power of the day is obtained. Furthermore, the total active power and total reactive power are distributed according to the ratio of each phase of corresponding bus in the improved IEEE-13 bus system, to obtain the simulated actual power of each phase of corresponding bus. Based on the injection Newton's method, the power flow is obtained, and the monthly TLL for 30 days can be got.

Method 2 [18]: Monthly TLL calculation based on hourly electricity

The simulation process is the same as Method 1, with the difference being that Method 1 uses daily electricity data, while Method 2 uses hourly electricity data to calculate 24 times in a day, therefore, the monthly TLL for 30 days can be got.

The proposed method: Monthly theory line loss calculation based on simultaneous power and electricity

The simulation process is the same as Method 1, with the difference being that Method 1 uses daily electricity data, while the proposed method in this paper uses

TABLE 3. Statistical results of line loss rate under three sampling scales in IEEE-13 buses distribution system.

results	Method 1			Method 2			The proposed method		
	10^3	10^5	10^7	10^3	10^5	10^7	10^3	10^5	10^7
Mean theoretical line loss rate	2.5236%	2.5188%	2.4761%	2.4322%	2.4011%	2.3965%	2.2957%	2.3107%	2.3187%
Standard deviation of TLL rate	0.1387%	0.1388%	0.1427%	0.1375%	0.1267%	0.1267%	0.1210%	0.1150%	0.1150%
synchronous line loss rate	2.3200%	2.3200%	2.3200%	2.3200%	2.3200%	2.3200%	2.3200%	2.3200%	2.3200%
line loss difference	0.2036%	0.1988%	0.1561%	0.1122%	0.0811%	0.0765%	0.0243%	0.0093%	0.0013%
percentage error	8.7759%	8.5689%	6.7284%	4.8362%	3.4957%	3.2974%	1.0474%	0.4009%	0.0560%

TABLE 4. Statistical results of line loss rate under three sampling scales IEEE-33 buses distribution system.

results	Method 1			Method 2			The proposed method		
	10^3	10^5	10^7	10^3	10^5	10^7	10^3	10^5	10^7
Mean theoretical line loss rate	3.6593%	3.6523%	3.5903%	3.5267%	3.4816%	3.4749%	3.3288%	3.3505%	3.3651%
Standard deviation of TLL rate	0.2011%	0.2012%	0.2012%	1.9936%	0.1837%	0.1837%	0.1757%	0.1668%	0.1668%
synchronous line loss rate	3.3640%	3.3640%	3.3640%	3.3640%	3.3640%	3.3640%	3.3640%	3.3640%	3.3640%
line loss difference	0.2953%	0.2883%	0.2263%	0.1627%	0.1176%	0.1109%	0.0352%	0.0135%	0.0011%
percentage error	8.7782%	8.5702%	6.7271%	4.8366%	3.4959%	3.2967%	1.0463%	0.4014%	0.0327%

hourly first and last power and electricity data to calculate 72 times in a day. Each hour is divided into three intervals of 20 minutes, therefore, the monthly TLL for 30 days can be got.

Based on the above three deterministic TLL calculation methods, the monthly TLL results are shown in Table 2.

According to the results shown in Table 2, the monthly TLL calculated by Method 1, Method 2 and the proposed method in this paper are 139.74kWh, 131.76kWh and 127.46kWh respectively. The synchronous line loss collected of the actual standard LVN is 124.72kWh, which is regarded as a standard reference line loss value, and its error is ignored. The difference between the three methods and the reference value is 15.02kWh, 7.04kWh and 2.74kWh, respectively, percentage errors are 12.04%, 5.60% and 2.16%.

Therefore, it can be seen that Method 1 has the largest calculation error, Method 2 has the second largest calculation error, and the proposed method in this paper has the smallest calculation error. The main reason is that the power load has significant fluctuations within a day. Using daily electricity data for calculation has a larger error, while using hourly electricity to convert a day into 24 periods is more optimal for calculation. However, in this paper, hourly first and last power and electricity data are used for calculation, and the calculation time scale is smaller. Therefore, it can better reflect the actual fluctuation of power load, fully utilize more abundant data, and its calculation results are more accurate.

(2) Monthly probability TLL calculation and analysis

Based on the improved IEEE-13 buses system and Monte Carlo simulation, the ARSM was used to generate 10^3, 10^5, and 10^7 sample to calculate the monthly probability TLL of LVN. Figure 6 shows the probability density curve results of the line loss rate using the proposed method under three sampling scales.

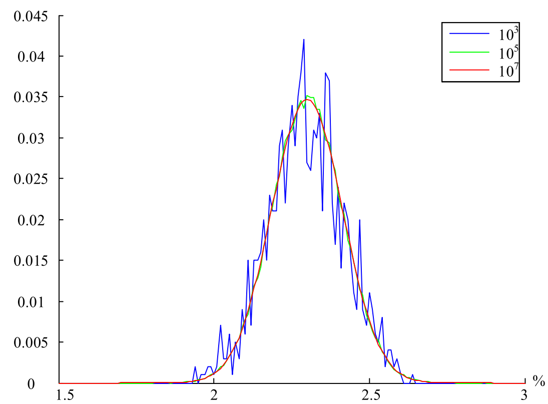

FIGURE 7. The probability density curve results of the line loss rate under three sampling scales.

From Figure 6, it can be seen that under three different sampling scales, frequency fitting was performed on the obtained results. Among the results, when the sampling scale is 10^3 times, the frequency distribution curve was the roughest; when the sampling scale is 10^5 times, the frequency distribution curve is relatively smooth; When the sampling scale is 10^7 times, the frequency distribution curve is smooth and infinitely approximates the Gaussian distribution curve. From the curves under the above three sampling scales, it can be seen that based on Monte Carlo simulation, the larger the sampling scale, the smoother and closer the results obtained are to the Gaussian distribution.

The statistical results of the mean and standard deviation of line loss rates for Method 1, Method 2 and the proposed method in this paper under three sampling scales are shown in Table 3.

As we all know, with the increase of sampling scale, the calculated average line loss rates will gradually approach the true values. Seen from Table 3, it can be seen that the average line loss rates obtained for Method 1, Method 2 and the proposed method in this paper under 10^7 sampling scale are 2.4761%, 2.3965%, and 2.3187%, respectively. Assuming that the synchronous line loss rate 2.3200% is a standard reference value in LVN, the difference in line loss percentage between the results obtained by the three methods and the reference value is 6.7284%, 3.2974%, and 0.0560%, respectively. From this, it can be seen that under the same sampling scale, the results obtained by the method proposed in this paper is closest to the reference value, and the error is smaller. At the same time, it can be observed that under different sampling scales, the difference in line loss rate of the method proposed in this paper is also the smallest, and as the sampling scale increases, the standard deviation of line loss rate tends to stabilize.

In order to prove the effectiveness of the proposed method in the larger IEEE standard distribution networks, further simulation is carried on IEEE 33 buses standard distribution system. Simulation conditions are consistent with IEEE 13 buses standard distribution system. The statistical results of the mean and standard deviation of line loss rates for Method 1, Method 2 and the proposed method in this paper under three sampling scales are shown in Table 4.

Seen from Table 4, it can be seen that the average line loss rates obtained for Method 1, Method 2 and the proposed method in this paper under 10^7 sampling scale are 3.5903%, 4.4749%, and 3.3651%, respectively. Obviously, the difference in line loss percentage of the proposed method in this paper are still smaller than Method 1 and Method 2. The results are basically consistent with those of IEEE 13 buses distribution system, which shows that the proposed method is still effective in other IEEE standard distribution networks as well.

VI. CONCLUSION

In this paper, a monthly probability TLL calculation method of LVN based on simultaneous power and electricity is proposed. First of all, the time interval of theory line loss calculation is shortened compared with the previous line loss calculation method based on daily electricity and hourly electricity, thus can improve the accuracy of TLL calculation. Secondly, by using the improved KCM and non-parametric Kernel density estimation, the load probability distribution model is established, and the ARSM is used to generate the power random samples of each user's load. Finally, based on the IEEE-13 buses and IEEE 33 buses distribution system, the simulation results showed that the proposed method can more accurately and effectively calculate the monthly probability TLL of LVN, which can help clarifying the space for reducing line loss, and providing theoretical basis and scientific support for formulating line loss reduction measures.

In the follow-up research, based on cross-platform multi-source data, the topology and parameter identification technology of LVN will be studied and a comprehensive decision-making platform for online line loss calculation and power grid management in the LVN will be developed, so as to automatically identify and display LVN topology, line losses in real time, and automatically generate line loss reduction strategies.

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YUNZHAO FENG is currently pursuing the bachelor's degree with China Three Gorges University. His research interest includes the optimization and scheduling control of integrated energy systems.

LIANGYU LONG is currently pursuing the bachelor's degree with China Three Gorges University. His research interest includes the optimization and low-carbon dispatch of integrated energy systems.

JIAYUE QIAN is currently pursuing the bachelor's degree with China Three Gorges University. His research interest includes the optimization and low-carbon dispatch of integrated energy systems.