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Application of Cluster Technique for Loss Estimation in Distribution Feeders via Limited Measurement Data

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ABSTRACT

To calculate the losses of distribution feeders, this paper uses an iterative method that is limited to restricted measurements. The approach presented in this paper uses bill data in addition to output information from a very small number of real-time measurements located on the secondary side of distribution transformers. This method attempts to estimate the load of distribution transformers injected into LV feeders. Energy losses for LV feeders are evaluated by first estimating the power and periodic energy injected to each of the LV feeders and then subtracting the total consumption bills from these estimated values. By using this method, the amount of energy loss is estimated. In this article, a new method called iterative power factor adjustment method is considered as a potential method for estimating losses. The power factor can be increased by repeatedly using evolutionary algorithms and including capacitors in the system. In order to reduce system losses and increase network effectiveness. In this paper, a new method for examining and evaluating Non-Technical Losses (NTL) is proposed. This method considers load estimation and limited measurement to place high priority feeders.

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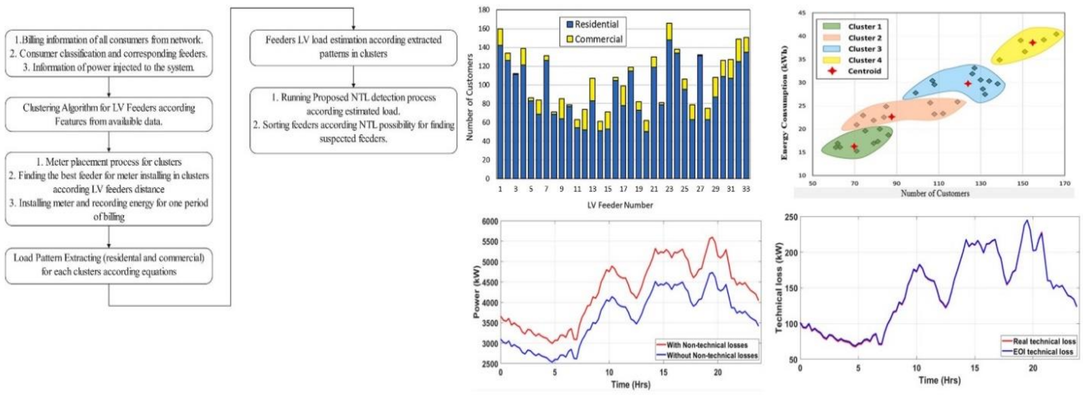
Graphical Abstract



NOMENCLATURE

e_{Tec}	the energy loss calculated for a daily cycle (kWh)	N_i	the number of time cycles in one day
P_{Ti}	the technical loss for the i-ohm load curve in the daily cycle (kWh)	T	the length of each time cycle in the daily load curve (in hours)
$error$	error between the energy values obtained by two methods (%)	$e_{Tec}\ EOI$	the energy calculated using the EOI method (kWh)
$e_{Tec\ Real}$	the energy calculated using the real technical loss curve method (kWh)		

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1. INTRODUCTION

Power loss is one of the biggest problems of power companies and the entire power industry. Loss of power at any moment increases the required capacity of power plants, especially during peak consumption, which itself requires a lot of investment to create power plant production capacity to cover power losses (1-5). Energy loss causes a significant amount of the produced electrical energy to be wasted instead of being sold to consumers, which, considering the cost of each kilowatt-hour of energy, causes great damage to power companies and the entire power industry. There are power losses in all parts of the electricity industry, including the production system, transmission network, and distribution network, but due to the extent of electricity distribution networks, it has the highest losses (6-9). Due to the low voltage level and high current of distribution networks, ohmic losses in the distribution sector are much more important than in transmission networks. Until the 90s, due to the lack of access to digital computers with suitable memory and high computing speed, most of the solutions provided were based on analytical methods and mathematical calculations (10, 11).

The issue of energy losses is one of the most important challenges of the electricity industry, and paying attention to its reduction is an inevitable necessity. In industrialized countries, since the beginning of the formation of this industry, i.e. in 1900 AD, attention has been paid to the issue of casualties and so far many efforts have been made in this field and good results have been achieved with various inventions. reducing non-technical losses in distribution networks and recovering lost electrical power in all types of distribution networks is of great importance in increasing reliability and reducing imposed costs (12, 13). The weak infrastructure of traditional networks and the high cost of installing equipment are the reasons for not being able to install measuring devices in all feeders. It should be noted that standard approaches to network loss assessment require detailed information about the network, including cable impedance, cable length, and load curves at each load point (14, 15).

2. RELATED WORKS

Yadav et al. (16) proposed loss estimation method clarifies the effects of CVR in terms of load and loss reduction. In this research, due to the passage of very high current at the head of the feeder line, the electrical losses caused by clamps used in some initial distances of the feeder have been evaluated. By extracting the current passing through the studied feeders and finally the number of connections in the overhead lines, the amount of electrical losses caused by them in all the feeders has been obtained. Finally, it was found that by modifying and removing the unnecessary clamps installed in the middle of the openings, a part of the electrical losses of the distribution lines can be reduced. Saeed et al. (17) investigated the causes of power losses from the point of view of power industry experts, and data mining techniques were used to classify different types of power losses. According to the climatic conditions and the amount of electric energy produced in each region and the multiplicity of related factors, the fuzzy decision tree classification method has been used. Velasco Rodríguez (18) assumed that there is a measuring device only in the upstream transformer and some end transformers of the distribution network. It is necessary to accurately predict the load in each feeder in order to get an accurate estimate of the non-technical losses that occur in each feeder. The lack of information in the unobservable network is the main challenge of the paper for load estimation. In this study, to overcome this issue, it has been used by other network information. De Santis et al. (19) introduced a method for estimating weak pressure network losses using available information. The information used in this method is available in the GIS system and does not require the installation of another measuring device.

Youn et al. (20) presented a new multipurpose objective function for locating the optimal location and capacity of distribution substations based on the service range, considering two important factors of reducing losses and improving the reliability of distribution networks. The proposed objective function includes all equipment construction and operation costs, loss cost and reliability index (unsupplied energy). The bee colony algorithm was used to optimize the proposed objective function to determine the capacity and optimal placement of posts in two sample distribution networks. By comparing the results obtained from the optimization of the proposed objective function with the bee colony algorithm with the results of other algorithms in two sample networks, it shows the efficiency and effectiveness of the algorithm and the proposed objective function. Bayat et al. (21) introduced a method for optimal placement of capacitors in distribution networks that lacks complete and accurate technical information. For this purpose, the reversibility feature of neural networks has been used. In the proposed method, capacitor values in the candidate channels are first selected by the genetic algorithm. Then, using the neural network, the amount of network loss is predicted for each capacitor state and returned to the genetic algorithm to select the best state. The neural network receives a number of feeder information such as active and reactive power, line length and location, and capacitor value as input and leads to losses as output. Therefore, none of the technical information of the network or feeder is required. With limited information from the distribution network, the optimal location and value of the capacitor can be suggested to reduce system losses. Despite the lack of complete and accurate technical knowledge, a method has been devised that is based on loss estimation and can be used to arrange capacitors in energy distribution networks in the most effective way possible (22). This paper provides estimates of network losses, each of which is obtained from data obtained from a specific part of the network. The genetic algorithm is first used to select the values of the capacitors installed in the candidate busses in the proposed approach. After that, the amount of network loss for each capacitor state is predicted using a neural network, and then the information is fed back to the evolutionary algorithm to select the optimal state.

In this paper, a new approach using the iterative method of power factor correction for loss estimation is presented. The power factor is improved by adding capacitors and repeatedly using evolutionary algorithms. so that it leads to reducing system losses and increasing network efficiency. the consumer billing data for a 30-day payment period is used as the basis for the implementation of the proposed technique. In addition to the billing data and the output information, a very small number of real-time measurements located on the secondary side of the distribution transformers were also utilized. These measurements were positioned on the secondary side of the distribution transformers. During this process, an effort is made to arrive at an estimation of the load that distribution transformers are pumping into LV feeders that is more accurate. The K-Means based clustering method has been used to clustering different loads in this study. To calculate the energy loss value for the LV feeders, first an estimate of the periodic power and energy that is injected into each LV feeder is made, and then this estimate is subtracted from the overall consumption bills. The most important advantages of this method are accurate and high-quality estimation of technical and non-technical energy losses, identification of transformers with non-technical losses, simplicity and easy understanding of calculations and the possibility of increasing the accuracy of the method. In this research, the necessary scientific articles and sources were first examined, and then the proposed method was simulated with Simulink/MATLAB software and compared with the results of some similar articles of this project.

3. METHODOLOGY

In this paper to estimate and evaluate power and energy losses, a comprehensive solution for more accurate estimation of energy loss components is provided. In this regard, by having the normal load pattern of different types of consumption, the feeder load pattern and power losses at maximum consumption are obtained. By extracting the estimated loss coefficient, the amount of technical energy loss is estimated. On the other hand, considering that the total energy loss is available; therefore, an approximation of the non-technical losses is calculated by dividing the technical energy losses from the total energy losses. Then, by estimating the technical losses of the network in the absence of non-technical losses, an estimate of the share of non-technical losses in causing technical losses as well as the transformers that suffer non-technical losses is obtained. Different methods are used to estimate losses, we can mention two main methods

3. 1. Measurement Method This method can be used when it is installed in all the input sources and output feeders of measuring devices. In other words, this method is applicable when the total input and output energy in the studied period is available because in this way it can be determining the amount of energy losses. One of the important points in such cases is how to be sure of the accuracy of the measuring equipment or how to be sure that the measured losses are consistent with reality.

3. 2. Calculation Method To determine the energy loss, it is necessary to calculate its amount with the help of load distribution. Load distribution in this method shows the maximum power loss in certain conditions. In such a case, the calculated losses only include Joule losses in the lines and pregnancy losses, and no-load transformers. In order to calculate energy losses from power losses, it is necessary to use special methods. By reviewing the papers presented in the field of calculation, estimation, and evaluation of losses, a variety of methods have been presented, which are generally based on measurement methods and calculation methods.

The main topics of loss calculation and measurement are as follows:

1. Methods of direct loss measurement which are based on meter installation and reading and customer service and sales system information and finally AMR system.
2. The method of calculating losses based on empirical relationships that results from the relationship between losses and load factor or losses and load.
3. 3. Using calculation methods using the load distribution program and modeling the details of the network information and the load model in the software.

4. PROPOSED METHOD

This paper identifies issues related to use peak demand and loss factor to predict energy losses. Based on this research, a limited measurement-based loss estimation method was presented using "loss coefficient" as a basic parameter to explain load changes in loss estimation. Additionally, a dataset of load curves from power companies was used to describe load curve parameters. Determining the practical applications of the proposed method and how to use the average demand and loss factor to improve cable selection has increased the accuracy of loss estimation in distribution transformers and improved the quality of information in loss estimation analyses. The evaluation of these losses in power networks is necessary for engineering and economic reasons. These cases are called "technical losses". Using the load flow algorithm is a common way to estimate these losses. To perform such operations (such as cable impedance, cable length and load curve at any point) a comprehensive understanding of the network is essential. But unfortunately, planning studies and primary distribution systems often do not have access to this information.

The mentioned problem is investigated and corrected in this article. In this context, the most common way to calculate losses is to estimate at the highest level of demand (using the finite measurement method), and then use the loss factor to predict the amount of energy lost. The loss factor is a parameter that shows the relationship between the losses that occur when the load reaches a maximum and the total energy lost by a network. When estimating energy losses, the use of peak demand and loss coefficients present challenges that must be overcome. For example, there is no clear correlation between peak demand and the amount of energy lost. Information-based loss estimation during peak demand is, in fact, an empirical method that must be modified and optimized for each different type of system. Furthermore, the maximum demand for a particular system is a variable that is subject to uncertainty and is usually evaluated less accurately than energy consumption. Consequently, it is important to avoid using peak demand as a basis for estimating energy losses. The flowchart of proposed Method is shown in Figure 1.

4. 1. Estimation of Energy Loss with a Loss Factor

In this section, some of the pitfalls of calculating energy losses using peak demand information and loss factors are highlighted. In particular, these errors are shown when the load factor is used to obtain the loss factor, which is the most frequently used method. In this context, the following topics are very important

- Measurement of demand and its consequences in the assessment of maximum demand
- Random nature of peak demand
- Relationship between loss factor and load factor

4. 2. Estimation of Load Curve Parameter

In this section, the parameters of the database of load curves related to Iraqi distribution companies in Badra region (about 10,000 customers) are evaluated. Each load curve consists of 96 intervals and each interval lasts 15 minutes. The load curve database is discussed in Table 1. As a result, load curves were obtained from loads well as transformers. The measured points in this table are known as MP, while the load curve is denoted by LC. In Table 2, the statistics of the following load curve parameters are presented: load factor (LF), loss factor, constant k, CV and load service capacity (LSC). As expected, values across the board show significant variation.

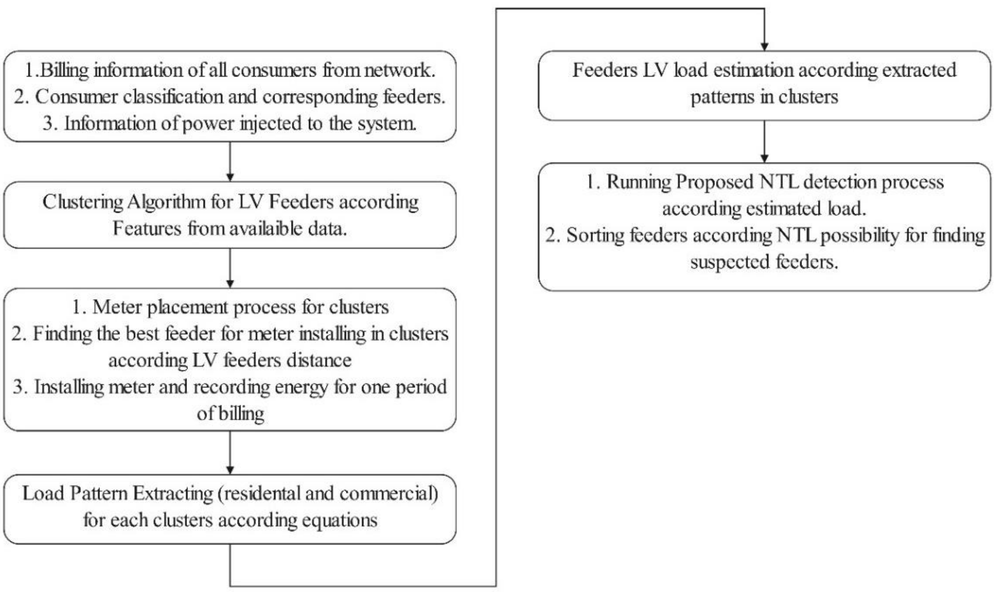

Figure 1. Flowchart of Proposed Method

TABLE 1. Load Curve Data Bank

	HV	HV/MV	MV	MV/LV	LV	Total
Number of LCs	12590	77934	111211	24692	233025	459452
Number of LCs	417	2469	3989	2004	18495	27374

TABLE 2. Statics of Load-Curve Parameters (P.U.)

		HV	HV/MV	MV	MV/LV	LV
	Mean	0.8	0.68	0.56	0.46	0.29
	Min	0.01	0.01	0.01	0.01	0.01
LF	Max	1	1	1	1	1
	σ	0.17	0.13	0.21	0.16	0.149
	CV	0.22	0.18	0.37	0.35	0.65
	Mean	0.69	0.51	0.42	0.28	0.17
	Min	0.01	0.01	0.01	0.01	0.01
LSF	Max	1	1	1	1	1
	σ	0.21	0.15	0.22	0.15	0.16
	CV	0.3	0.3	0.51	0.52	0.94
	Mean	0.13	0.12	0.29	0.21	0.29
	Min	0	0	0	0	0
K	Max	1	1	1	1	1
	σ	0.17	0.11	0.23	0.17	0.19
	CV	1.32	0.91	0.77	0.79	0.66
	Mean	0.21	0.26	0.56	0.56	1.05
	Min	0	0	0	0	0
CV	Max	9.8	9.8	9.8	9.8	9.8
	σ	0.43	0.31	0.53	0.45	0.79
	CV_{CV}	2.04	1.21	0.95	0.81	0.76
	Mean	1.23	1.16	1.59	1.52	2.72
	Min	1	1	1	1	1
LSC	Max	97	97	97	97	97
	σ	2.87	1.78	2.76	2.08	4.67
	CV	0.43	0.65	0.58	0.73	0.58

A random selection of 30,000 load curves from the database was used to create the sample as shown in Figure 2, which is a plot of load factor vs loss factor in the LV part of the load curves. The load factor is often utilized in order to determine the degree of change present in a load curve. Even though this presumption is only partially accurate, the load factor is nevertheless a reliable indicator.

The Pearson correlation value between the load factor and the coefficient of variation (CV) in load curve database is about -0.75, which indicates that there is a strong association between the two variables. However, the CV gives more information about changes in the load curve and has the advantage of being less sensitive to the amount of time intervals in the load curve than the load factor does. This makes the CV superior to the load factor. A sample of 10,000 load curves is taken with 96-time intervals and merged them into curves with 24-time intervals. After doing so, we discovered that the mean absolute percentage error (MAPE) for load factor was32%, while the MAPE for CV was 12%. Because of this, CV is less susceptible to changes in the number of load curve periods than load factor. It is intriguing to

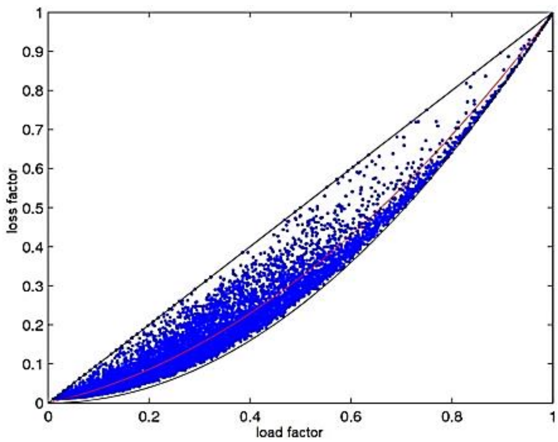

Figure 2. Loss factor (in LV segment) versus Load factor

analyze how much each term contributes to the total amount of energy that is lost (the hypothetical situation is a line-like LC behavior). The CV parameter of the load curves contained in the database, also known as the LSC parameter, has an exponential distribution over all sections.

5. SIMULATION RESULTS

In this particular case study, there are 33 LV feeders supplying a total of 3495 single-phase consumers. Among them, 3097 are residential consumers and the rest are commercial consumers. Figure 3 shows the total number of residential and commercial customers connected to each LV feeder. As mentioned earlier, this study considered four characteristics of LV feeders that may be used in clustering. Figure 4 shows the impact of 10% increase in load imbalance in LV feeders. Also, Figure 5 shows a graphical representation of the clustering of consumers in the network.

Figures 6 and 7 show the daily average P/Ps recorded by each cluster during the study. In each figure, the maximum P/P is shown along the x-axis. To perform a deeper analysis of the patterns, these profiles have their peak values subtracted before converting to unit values.

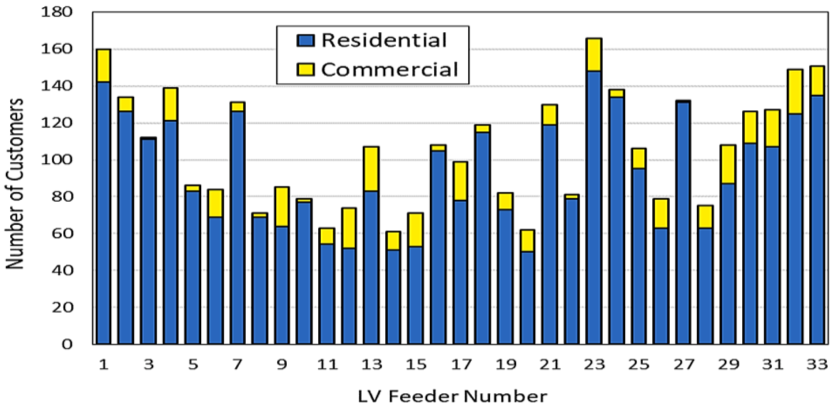

Figure 3. The number of customers in the case study

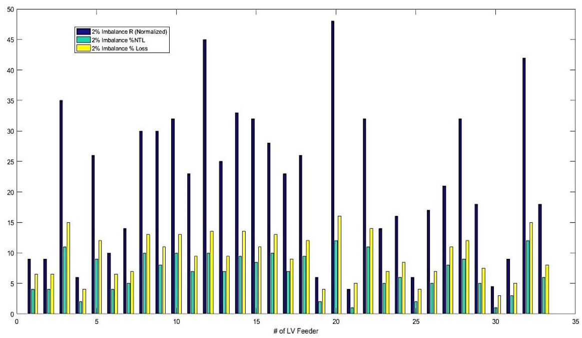

Figure 4. Impact of 10% increase in load imbalance in LV feeders

These patterns, as shown by the data, are derived from the consumption probabilities of customers belonging to each class in all clusters. Figure 8 shows a comparison between the load estimation method presented in this paper and a load allocation technique presented by Han et al. (23). It can be seen that the proposed method has good results and high accuracy. This figure shows a comparison of the average load profile (within 24 hours) of low voltage (LV) transformers placed in four buses.

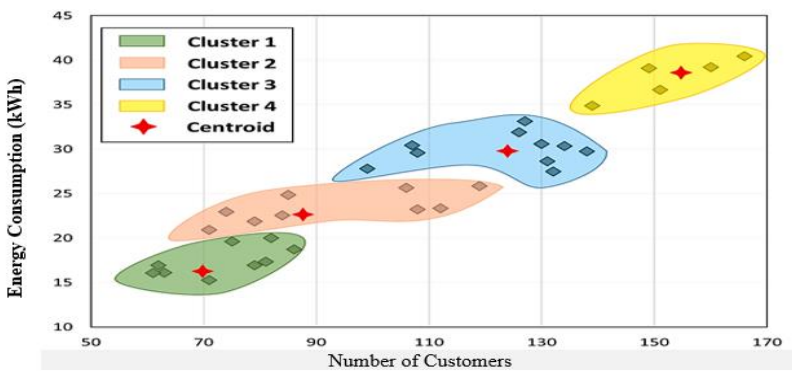

Figure 5. Graphic representation of consumer clustering

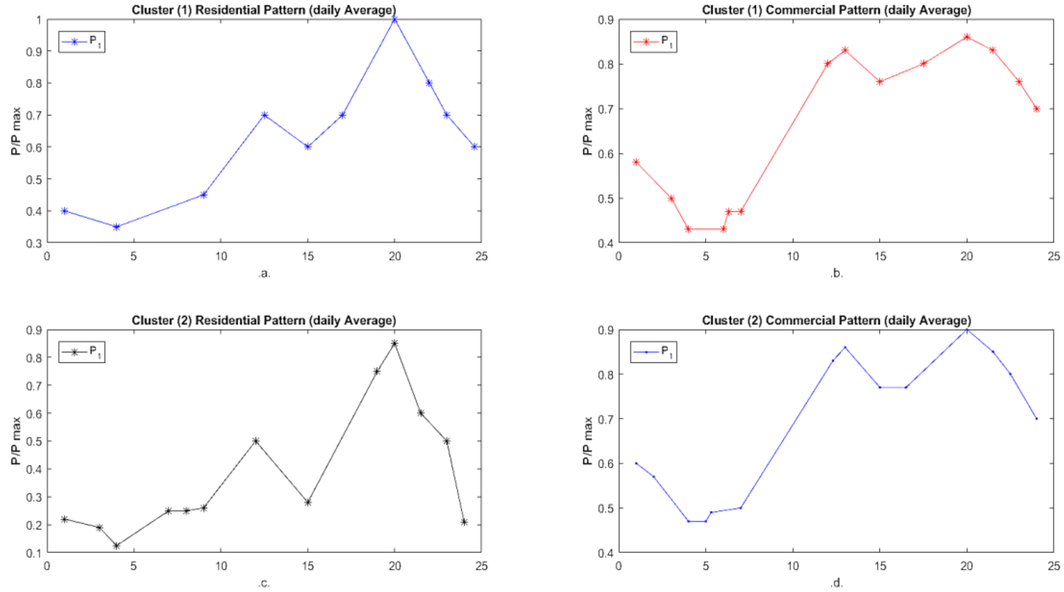

Figure 6. Extracted P/Ps of Clusters 1 and 2

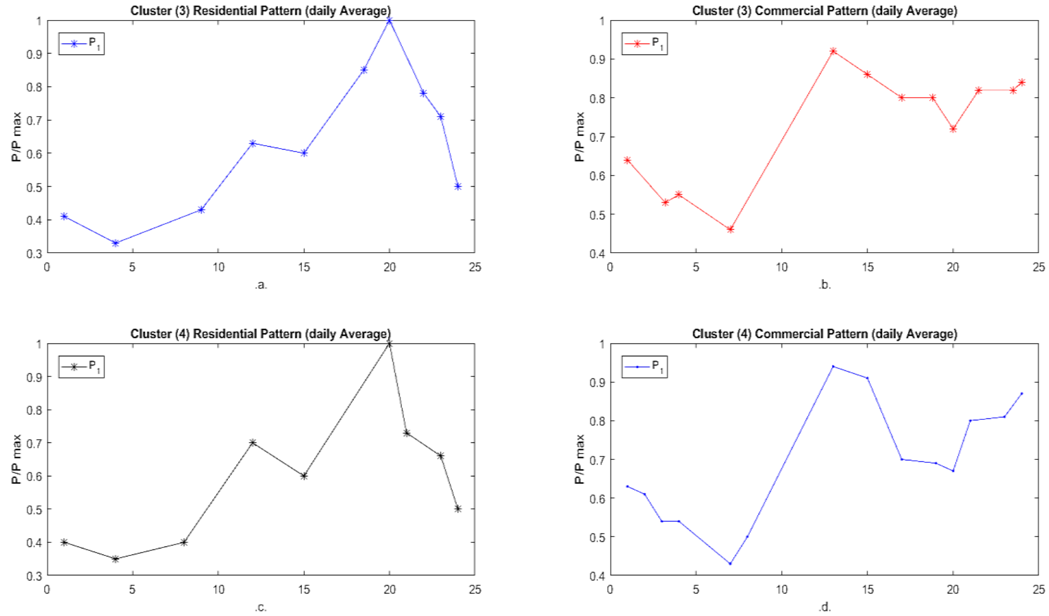

Figure 7. Extracted PLPs of Clusters 3 and 4

As it is known, in these feeders, despite the installation of measuring devices, the amount of load obtained from the load allocation method is not equal to the real value of the load.

As seen, the results obtained with the load allocation approach have more error compared to the results obtained using load estimation. Figure 9 shows the error percentage of these two methods in different bases. This comparison clearly shows the superiority of the proposed method. Assuming α = 0.01, it facilitates the calculation of R values for each LV feeder. After that, the values calculated for the LV feeds are sorted in ascending order. To show the flexibility of the index that was created, the value of α is varied (0.05, 0.015, and 0.02) and then the R index for each of these three values is compared in Figure 10. Also, in Figure 11, a comparison is made between %Loss, %NTL, and R.

The studied network was re-implemented with different degrees of unbalance between phases so that the effects of network unbalance can be investigated with the help of the proposed NTL detection method. After the completion of this operation, the total consumption of the low-pressure feeders remained constant, while the single-phase loads became more unequal. For this reason, the results of energy loss as well as the R index are shown in Figures 12 and 13, respectively, with an increase of 2% and 10% in the phase imbalance applied to the network. According to these figures, it was found that an increase in network imbalance leads to an increase in the amount of energy lost in the network. Also, Figure 14 shows the accuracy of load estimation in different buses.

In the proposed method, we need historical data about the amount of monthly energy injected. In addition, information on water and electricity bills related to consumers will also be used. The total amount of energy loss in the network formula connected to this section can be determined by subtracting these two parameters from each other.

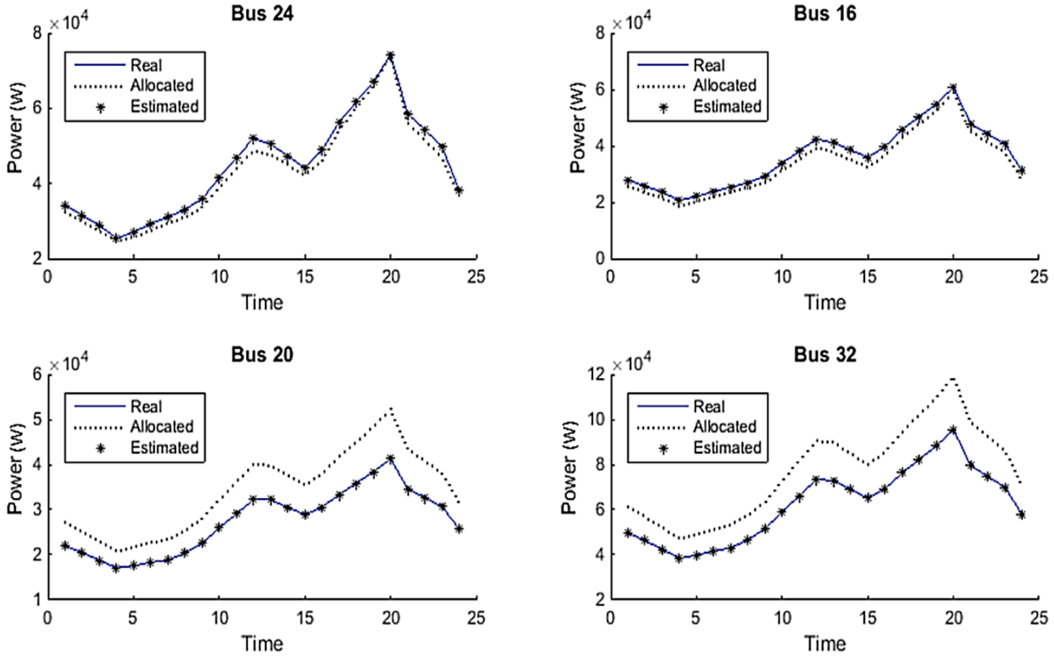

Figure 8. Results of load estimation of Transformers (daily average) (Allocated: [23])

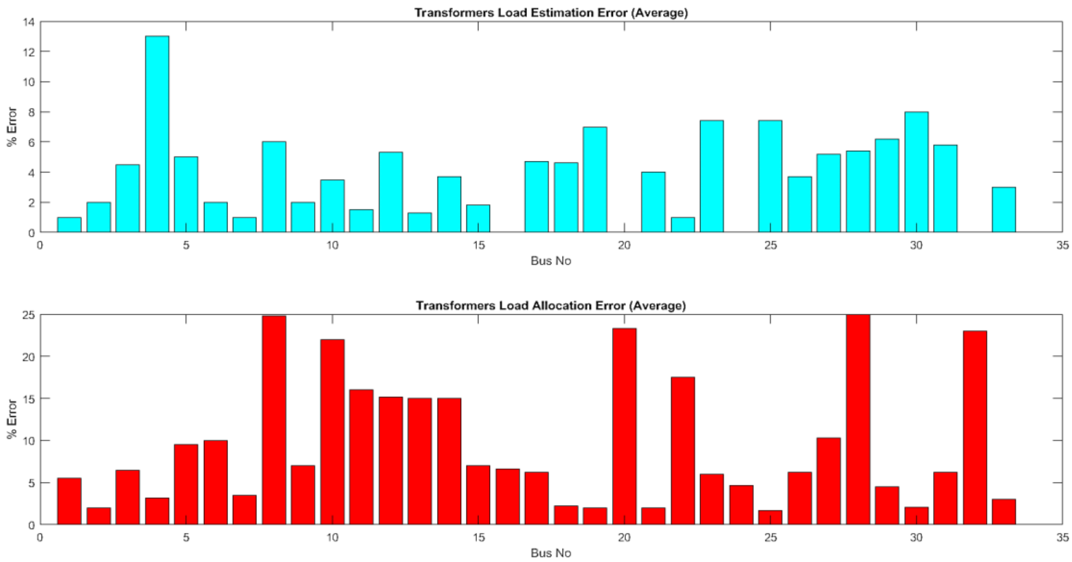

Figure 9. Comparison of the proposed transformers load estimation and Allocated [23] error

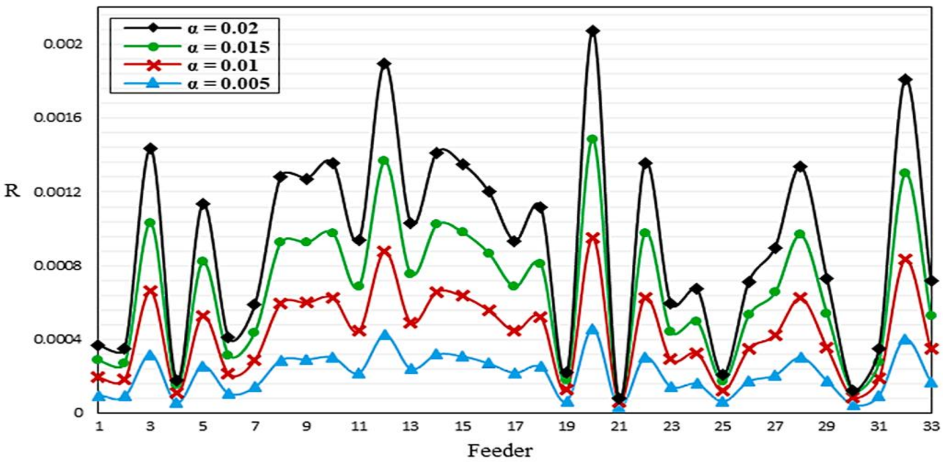

Figure 10. NTL possibility per capita for LV feeders

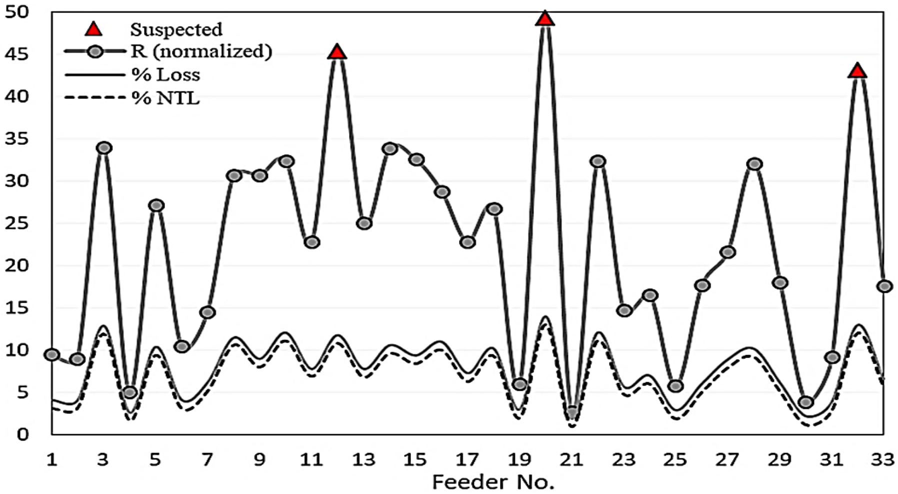

Figure 11. Comparison of %Loss, %NTL, and R in LV feeders

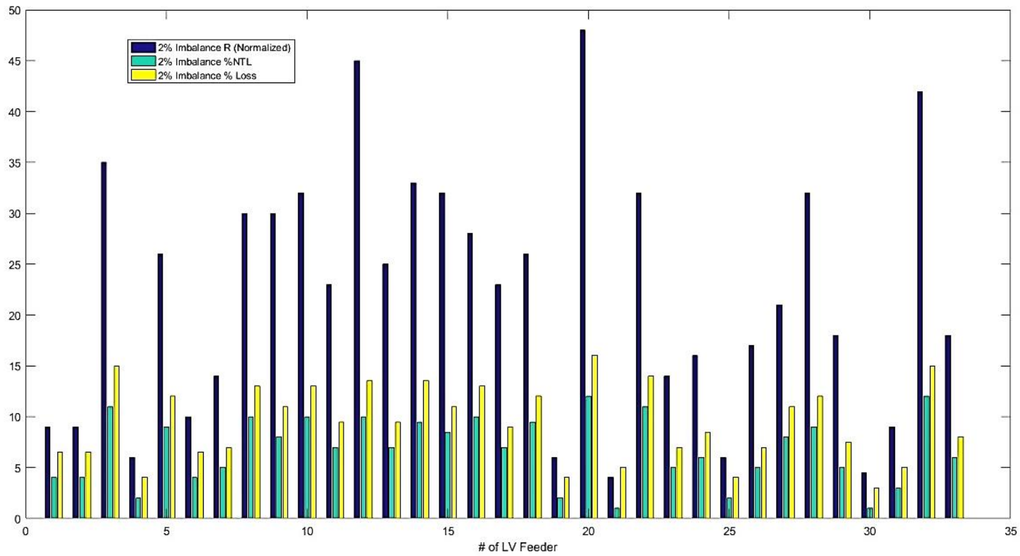

Figure 12. Low Voltage feeders after 2% load balance increase

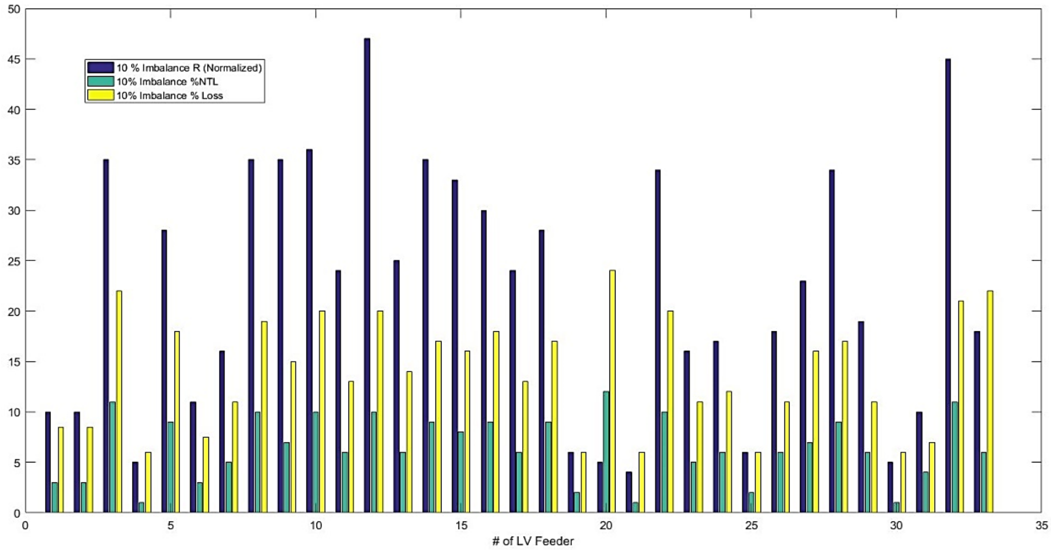

Figure 13. Impact of 10% increase in load imbalance in LV feeders

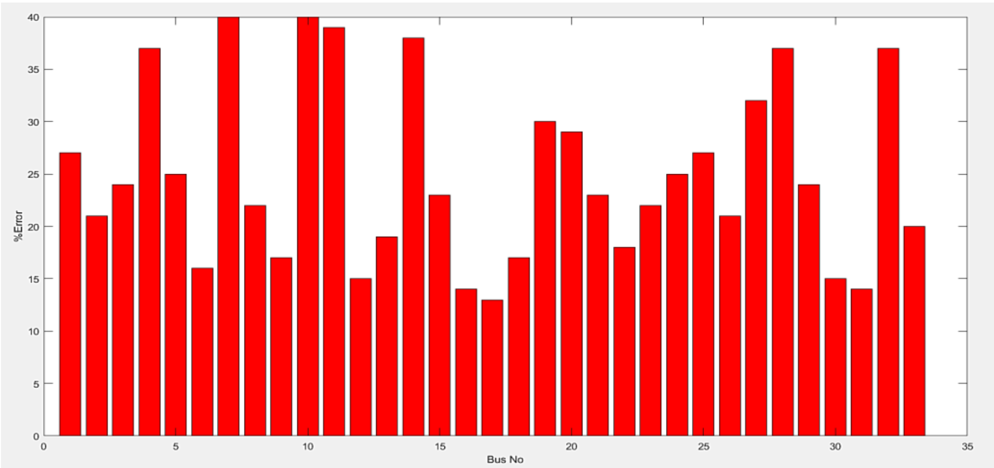

Figure 14. The accuracy of Load estimation for geographical division

When the main system is considered, non-technical losses are arbitrarily added to the load buses (in a ratio varying from 0 to 40%), following the base loads, which are given variables. After going through this process, the total injected active power curves for 24 hours were obtained (as shown in Figure 15 for the scenarios where only normal energy consumption (billing) is considered and irregular consumption which refers to the consumption, which includes non-technical losses).

With this scenario, the valves of the voltage regulating transformer are kept in their original position in both loading scenarios are shown in Figure 15. Along the system load curve is shown in Figure 16, a larger voltage drop was detected due to the increase in load that occurs when non-technical losses are present.

Considering the diurnal mode simulation in OpenDSS, an EOI curve representing each loading condition was calculated at 15-minute intervals, for a total of 96 intervals, as shown in Figure 17.

At this point, before presenting the results, the difference between the two loss values that will be presented is highlighted:

1. Real technical losses, ie. losses calculated from the implementation of load flow when adding random irregular loads to the system at the base.

2. EOI technical losses, which are also called losses that are calculated using the EOI values are shown in Figure 17, for load conditions only considering the billed demands, after adjusting the load power factor and using the measurements to obtain the total injection current indicating the load condition; including any losses caused by technical issues. As a result, a comparison between the actual technical loss and the EOI technical loss curve may be seen in Figure 18. This figure shows the close

relationship that exists between the two curves at each sampled time point (which shows the high accuracy of the proposed method for calculating losses).

Considering the power loss values presented in Figure 18, the daily energy loss can be obtained using following equation:

$$e_{Tec} = \sum_{i=1}^{N_i} P_{Ti} . T \quad (1)$$

Both the EOI method and the load current routine are used to calculate the percentage error between the calculated energy values (Equation 2). When the values of the curves shown in Figure 18 are considered, the obtained inaccuracy is 0.5827%.

$$error = \left(\frac{e_{Tec\,EOI} - e_{TecCeal\_}}{e_{Tec\,Real}} \right) \cdot 100 \quad (2)$$

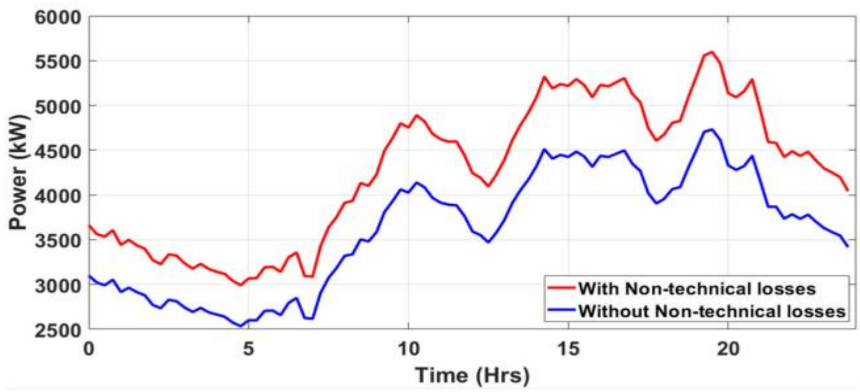

Figure 15. Active power injected into the IEEE-123 bus test system in both loading conditions: without irregular loads (blue) and with irregular loads (red)

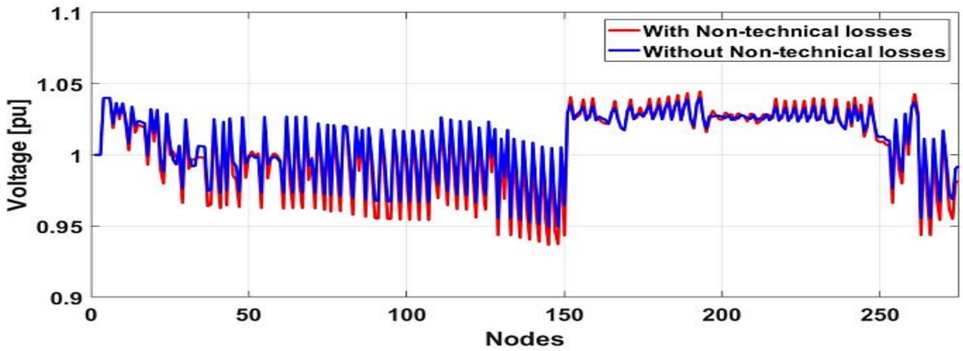

Figure 16. IEEE 123 bus test system voltage profiles at all nodes for peak load at 7:45 PM, considering non-technical losses (red) and no non-technical losses (blue)

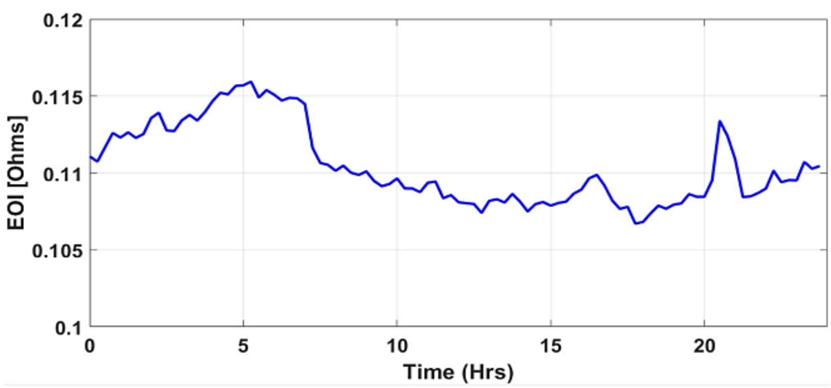

Figure 17. EOI curve during one day to calculate total technical losses for loading conditions with irregular loads

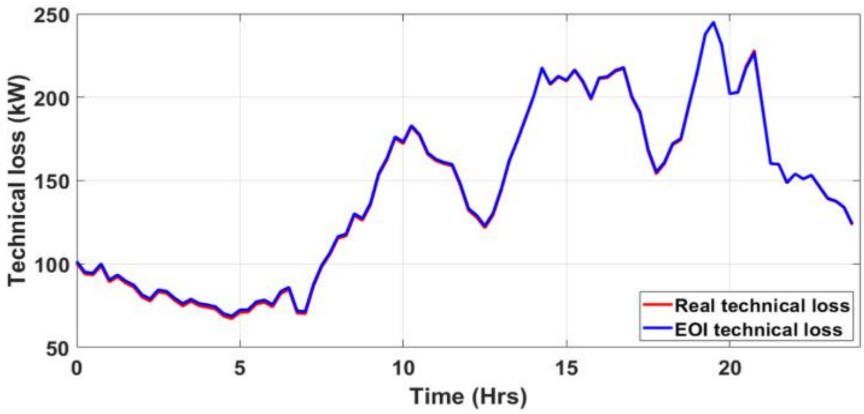

Figure 18. Real technical losses (red) and technical losses calculated with the help of EOI (blue)

6. CONCLUSIONS

In this paper, considering load estimation and limited measurement to find high-priority feeders, a new approach to investigate and evaluate NTL is presented. According to the obtained results and the average error in the load estimation method compared to the normal methods. There has been a drop of about 5.5 to 6%. According to the obtained results, in low voltage (LV) feeders, whose transformer is far from the center of the corresponding cluster, the load estimation error is about 13%. It is also known that in about 80% of the feeders, the load estimation error is less than 6%. Therefore, the method of placing the above meter is much more suitable than placing a random meter. Since the plan extracted for the placement of the meter is very important and necessary in the loss estimation method, this level of accuracy has a great impact on the estimation results of technical and non-technical losses. According to the mentioned contents and the simulation output, the proposed method for evaluating NTL is efficient and appropriate. Also, in the evaluation stage of NTL in weak pressure feeders, it was found that the value of R index in feeders' is somewhat higher than others. Therefore, they can be considered the first priority group. In future studies, this method can be developed as an example considering the presence of distributed generations in the distribution networks. This section is not mandatory but can be added to the manuscript if the discussion is unusually long or complex.

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Persian Abstract

چکیده

برای محاسبه تلفات فیدرهای توزیع، این مقاله از یک روش تکراری استفاده می کند که محدود به اندازه گیری های محدود است. رویکرد ارائه شده در این مقاله از داده های صورتحساب علاوه بر اطلاعات خروجی از تعداد بسیار کمی از اندازه گیری های بلادرنگ واقع در سمت ثانویه ترانسفورماتورهای توزیع استفاده می کند. این روش تلاش می کند تا بار ترانسفورماتورهای توزیع تزریق شده به فیدرهای LV را تخمین بزند. تلفات انرژی برای فیدرهای LV ابتدا با تخمین توان و انرژی دوره ای تزریق شده به هر یک از فیدرهای LV و سپس کم کردن کل صورتحساب مصرف از این مقادیر تخمینی ارزیابی می شود. با استفاده از این روش میزان اتلاف انرژی تخمین زده می شود. در این مقاله روش جدیدی به نام روش تعدیل ضریب توان تکراری به عنوان روشی بالقوه برای برآورد تلفات در نظر گرفته شده است. ضریب توان را می توان با استفاده مکرر از الگوریتم های تکاملی و گنجاندن خازن ها در سیستم افزایش داد. به منظور کاهش تلفات سیستم و افزایش اثربخشی شبکه، در این مقاله روش جدیدی برای بررسی و ارزیابی تلفات غیر فنی (NTL) پیشنهاد شده است. این روش تخمین بار و اندازه گیری محدود را برای قرار دادن فیدرهای با اولویت بالا در نظر می گیرد.