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GESS-based technical loss estimation for sustainable power networks

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ABSTRACT

In the pursuit of global environmental sustainability, minimizing technical losses (TL) in power distribution networks has become a key priority for utility providers. Despite numerous advancements, precise loss estimation remains a challenge due to dynamic network conditions, complex configurations, and varying parameters such as load patterns and system topology. This issue is critical, as reducing TL not only enhances distribution efficiency but also contributes to lowering greenhouse gas (GHG) emissions. This study aims to develop and demonstrate a robust method for estimating TL aligned with the global environmental sensing and sustainability (GESS) principles. The proposed approach integrates an advanced loss estimation sequence comprising peak power loss (PPL), load loss factor, and an energy flow model. It is applied to real case studies, enabling assessment of both feeder and transformer losses. Results highlight the impact of key parameters including transformer capacity factor, cable length, load factor (LF), and loss factor on overall losses. Furthermore, the method facilitates quantification of environmental and economic impacts, revealing that both carbon footprint and cost rates are highly sensitive to total energy losses. This work underscores the significance of accurate TL estimation in promoting environmentally and economically sustainable power distribution systems.

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1. INTRODUCTION

Sustainability in electrical power systems has become a global concern due to the rising impact of greenhouse gas (GHG) emissions, largely driven by fossil-fueled generation and inefficient distribution networks [1]-[3]. A significant contributor to this inefficiency lies in technical energy losses (TL), especially within power distribution networks, where losses negatively impact operational efficiency, raise investment costs, and increase GHG emissions. Consequently, the environmental and economic evaluation of the distribution network relies on estimating energy losses [4]. This is because a reduction in losses directly corresponds to a decrease in CO_2 emissions [5]. Furthermore, the amplified power loss adversely affects the overall efficiency of the power distribution system [6]. In Malaysia, electric power transmission and distribution losses account for approximately 6% of output, with distribution losses being the major contributor [7]. Even marginal improvements in efficiency can result in substantial carbon reduction and significant financial savings. This highlights the urgent need for accurate, scalable, and sustainable TL estimation methods.

Several past studies have addressed that improving the energy efficiency of existing power delivery systems by managing energy demand and minimizing electrical losses is one of the most cost-effective strategies for meeting rising demand and reducing environmental impact [8]-[10]. However, designing networks based solely on peak demand is costlier than considering energy losses, leading utilities and regulators to actively explore loss mitigation strategies [8], [10]. In addition to these findings, other studies have emphasized the role of energy efficiency in reducing electricity tariffs and encouraging more responsible energy consumption through demand-based pricing mechanisms [11]-[13]. Nevertheless, existing TL estimation methods remain limited in terms of scalability, data requirements, and practical implementation [14], [15].

For instance, the method by Rao and Deekshit [16] relies on load flow simulations and feeder-level input measurements, making it labor-intensive and difficult to scale due to the need for repeated modeling and data logging. Similarly, Khodr *et al.* [17] proposed a statistical classification of TL based on extensive simulations, but the process is complex and data-heavy. Although these approaches yield reliable results, they are often limited by high data requirements, complex computations, and lack of scalability especially for large or dynamically changing networks. Furthermore, their long-term feasibility and alignment with sustainability goals are rarely evaluated. From this perspective, energy loss estimation must evolve to support the principles of global environmental sensing and sustainability (GESS), which emphasize solutions that are intelligent, resource-efficient, and environmentally conscious.

Thus, this paper introduces a novel, streamlined calculation sequence method for estimating TL, which requires minimal data input and computational effort, making it particularly suitable for large-scale deployment in practical environments. The approach involves a simplified analytical technique based on fundamental energy distribution equations, incorporating historical load profiles and sector-specific tariffs. By segmenting the network into feeder and transformer components, the method enables separate yet complementary loss evaluations. This structure allows for quick, scalable assessments without the need for complex simulations or detailed real-time data. The main contributions of this study are threefold:

- The development of a simplified, scalable TL estimation method that integrates key parameters such as transformer capacity factor, load loss factor, cable length, and peak power loss (PPL) within a lightweight yet systematic framework.
- The application and validation of this method through real-world case studies to demonstrate its practical effectiveness.
- A comprehensive evaluation of its environmental and economic implications, aligning with the principles of GESS.

To the best of our knowledge, this is the first TL estimation model explicitly formulated for large-scale, GESS-aligned deployment, offering dual benefits of reduced carbon emissions and cost-efficient energy management. The remainder of the paper is organized as follows: section 2 the proposed methodology. In section 3 discusses the results using case studies. In section 4 concludes with insights and future directions.

2. METHOD

This section outlines the complete procedure used to estimate TL in a medium voltage (MV) radial distribution network. The approach integrates real-world network parameters, simplified analytical expressions, and energy flow modeling. The methodology is designed for scalability and alignment with GESS principles.

2.1. Feeder configuration and data acquisition

The MV distribution network operates in a radial configuration, where energy flows unidirectionally from the transmission/distribution interface substation (TDIS) through outgoing feeders to the connected loads. This structure simplifies monitoring and control, with energy meters at the substation and ammeters on each feeder facilitating data collection. This configuration, which is illustrated in Figure 1, facilitates the straightforward application of the technical loss (TL) estimation framework due to its predictable energy flow path. It is particularly well-suited for implementing the proposed TL estimation method, showing a generic radial distribution feeder with *n* feeder sections [18].

Power losses, particularly I^2R losses, are calculated using a load-flow-inspired method. During the period, T, the load for any i^{th} feeder section ($P_f^i(t)$), can be obtained by adding all the loads at each downstream load point ($P_L^i(t)$). When there are *n* feeder sections and load points, the load profile for the first feeder section can be calculated as the coincident sum of all load profiles at load point 1 to *n*, as in (1).

$$P_f^i(t) = P_L^i(t) + P_L^{i+1}(t) + \cdots + P_L^n(t), for\ all\ t = 0 \ldots T \quad (1)$$

Energy adjustment variables or factors (cable length, current infeed) are used to estimate the energy inflow to MV feeders based on this energy flow model. The initial idea step is to calculate the TL of the feeder which has been modified based on the feeder of interest using the formula depicted in the next sub-section.

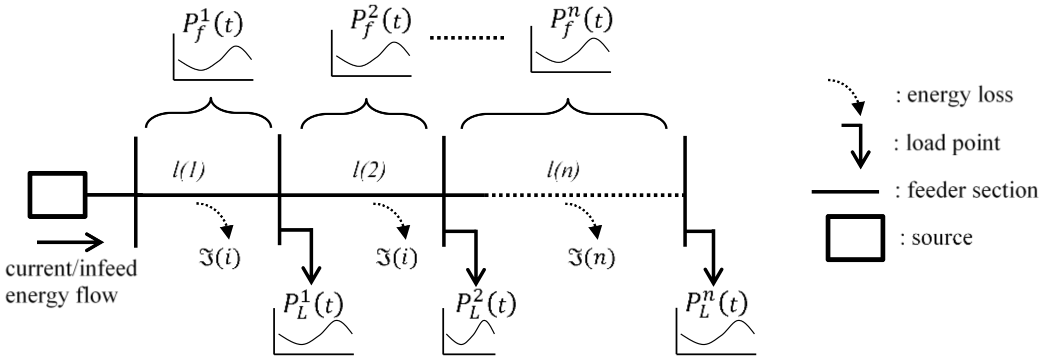

Figure 1. Single line model of radial distribution feeder with n feeder section [18]

2.2. Technical loss estimation in feeder

To estimate energy inflow (E), compute the estimated peak demand. Initially, the calculation of the estimated peak demand, denoted as P(W) at 11kV, is derived using (2), where the power factor, *pf*, and maximum current, I_{max} are obtained from the load profile. Next, the load factor (LF) is determined utilizing a representative load profile as in (3). In this equation, the LF for the feeder section is computed as the ratio of the average power demand, $P_{average}$ to the maximum power demand P_{max}. Notably, the selection of the feeder LF is influenced by the combination of customer-type loads occurring concurrently.

$$P = \sqrt{3} \times 11k \times pf \times I_{max} \quad (2)$$

$$LF = \frac{P_{average}}{P_{max}} \quad (3)$$

The estimation of infeed energy, denoted as E (MWh/month) for a month, is determined in (4) using the estimated peak demand and the LF. Here, the unit of P is in Watt, 30 represents the number of days in a month, and 24 represents the number of hours in a day. Subsequently, the corrected infeed energy (MWh/month) is established by applying a correction factor. Following that, the coefficient for PPL is derived using the base case feeder. The length correction factor is computed by multiplying the PPL equation with the ratio of the length of the specific feeder of interest, l_i to the length of the base case feeder, l_b, as illustrated in (5).

$$E = P \times LF \times 30 \times 24 \quad (4)$$

$$PPL_b = \frac{l_i}{l_b} \times \{a\rho_i^3 + b\rho_i^2 - c\rho_i - d\} \quad (5)$$

In (6) computes the loss factor, denoted as load fluctuations (LsF), using the LF of the feeder section and the coefficient α for LsF. In this context, the coefficient is specifically set at α=0.25. The 30-day energy losses denoted as EL in MWh can be estimated for each i^{th} feeder section by considering its PPL, LsF, and the monthly period as shown in (7). Ultimately, as outlined in (8), the overall energy losses for the feeder, denoted as EL_f, can be computed by summing up the energy losses of each feeder section, represented as EL_i. The total energy losses in MWh are determined by summing up the losses across all feeder sections.

$$LsF = \alpha \cdot LF_i + (1-\alpha) \cdot {LF^2}_i, for\ all\ i = 0 \ldots n \quad (6)$$

$$EL = PPL_b \times LsF \times 30 \times 24, for\ all\ i = 0 \dots n \quad (7)$$

$$EL_f = \sum_{i=1}^{n} EL_i \quad (8)$$

2.3. Technical loss estimation in transformers

Transformer losses are computed as the sum of no-load (NLL) and full-load losses (FLL). Based on values validated for Malaysian systems [19], NLL and FLL are assumed to be 1 kW and 4 kW respectively. Following this, the power unit in MW is converted to energy units in MWh, as expressed in (9) and (10). E_{NLL} is the energy of NLL, P_{NLL} shows the power of NLL, E_{FLL} indicates the energy of FLL, and P_{NLL} is the power of NLL. The total energy losses (MWh) are the summation of the NLL and FLL in energy unit as in (11). Overall, based on the adjusted energy inflow in the feeders, the feeder TL and transformer TL of the complete network are calculated. Finally, the whole process is repeated for the following network under study.

$$E_{NLL} = P_{NLL} \times 30 \times 24 \quad (9)$$

$$E_{FLL} = TCF^2 \times P_{FLL} \times LsF \times 30 \times 24 \quad (10)$$

$$E_{TL} = E_{NLL} + E_{FLL} \quad (12)$$

Figure 2 presents a summarized flowchart of the feeder TL estimation sequence, while Figure 3 shows a summarized flowchart of the transformer loss estimation method.

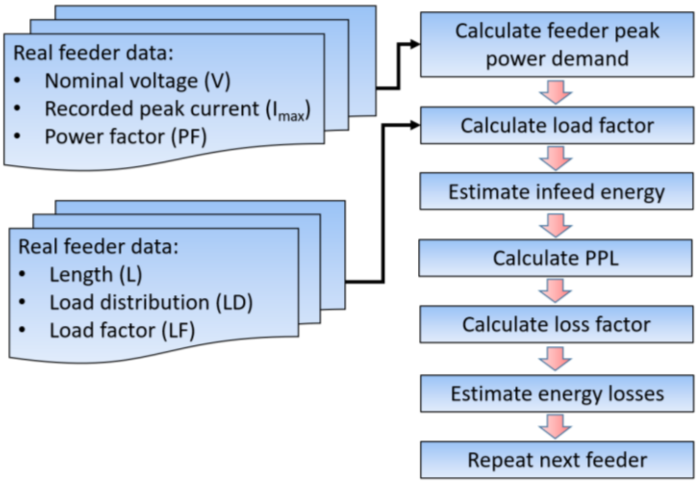

Figure 2. Feeder TL estimation method

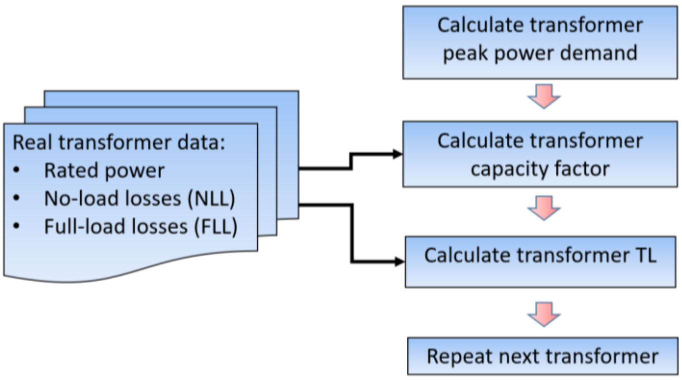

Figure 3. Transformer TL estimation method

2.4. Environmental and economic viewpoint towards energy losses

Calculating the carbon footprint as (12) is crucial for conducting environmental impact assessments, providing insights into the extent of GHG emissions linked to specific activities or entities. To quantify the environmental impact, CO_2 emissions due to energy losses are estimated using the national emission factor (0.741 kg/kWh), reports by Sustainable Energy Development Authority (SEDA) and Suruhanjaya Tenaga (Energy Commission) [20].

$$Carbon\ footprint = Total\ TL \times Emission\ factor \tag{12}$$

Then, the economic losses are calculated using area-specific tariffs (tariff A for residential, tariff C1 for commercial, and tariff E1 for industrial consumers). Typically, the primary contributors to the total energy consumption are the commercial and industrial sectors, succeeded by residential, transportation, and so forth [21]. In this case study, which encompasses residential, industrial, and commercial areas at 11 kV, the pricing calculations differ based on the area type. Tariff C1 is applied to commercial areas, and Tariff E1 is utilized for industrial areas. However, in the residential context, where the 11kV line does not directly supply power to the houses, regardless of whether it is a single-phase or three-phase connection, the electricity needs to be stepped down before entering the residence. Essentially, tariff A is employed for pricing calculations in the residential area. These reflect real billing categories from Malaysian energy pricing structures. Figure 4 outlines the cost and carbon footprint evaluation process.

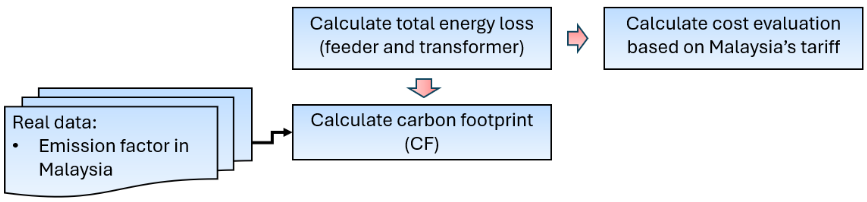

Figure 4. Economic viewpoint method (including carbon footprint and cost evaluation)

2.5. Case study setup and parameter

To validate the method, two real-world networks (Case A and Case B) are evaluated using utility provided data. These case studies cover different load compositions, feeder lengths, and transformer setups. Also, the impact of carbon footprint and cost evaluation will be analyzed by the result of energy losses. The parameter summary is shown in Table 1.

Table 1. Real data of 2 different case studies (A and B)

Case study	A	B
Ratio (kV)	132/11	132/11
Energy (MWh)	10256.58	27092.79
Feeder MD (MW)	21.72	68.93
11 kV UG and OH feeder number	7	8
11 kV UG and OH feeder length (km)	64.30	50.75
Number of distribution transformer	47	62
Distribution transformer capacity	26	48.15
LV feeder number	103	195

3. RESULTS AND DISCUSSION

The results presented in Tables 2 and 3 illustrate a strong relationship between cable length and energy losses in both feeders and transformers. In both case studies A and B, feeder F11-01, which has the longest cable length, consistently exhibits the highest feeder and transformer losses, 11.20 MWh and 16.49 MWh in case A, and 18.83 MWh and 40.93 MWh in case B, respectively. In contrast, the shortest feeder, F11-05 in case A, and F11-03 in case B, demonstrates the lowest energy losses.

Figures 5 and 6 illustrate the relationship between estimated TL and four key parameters for case study A and case study B, respectively. These visual comparisons aim to highlight both consistent patterns and anomalies in how these variables influence losses across different distribution configurations. Figure 5(a) in both figures show a generally positive correlation between losses and cable length, which aligns with theoretical expectations since longer cables introduce greater resistance, thereby increasing TL.

Figures 5(b) and 5(c) demonstrate a similar trend in both case studies, where as LF and LsF increase, so do the losses.

Figures 5(a) and 6(a) confirm this trend graphically, reflecting a linear relationship between cable length and losses. The correlation between cable length and losses tends to follow a linear pattern, indicating that as the cable length extends, losses proportionally escalate. This is supported by the theory that the introduction of longer cables introduces additional resistance, leading to increased energy losses [22], [23]. These observations validate the study's objective of accurately estimating losses and underscore the importance of optimized cable planning in loss reduction.

Table 2. TL estimation result of case study A

11kV feeder number	Length (km)	Estimated MD(MW)	LF	Infeed Energy (MWh/month)	PPL base (MW)	LsF	Feeder losses (MWh)	No of tx.	Power (MW)	TCF	Tx. losses (MWh)
F11-01	11.33	2.81	0.70	1807.18	0.03	0.55	11.20	8	1.31	2.61	16.49
F11-02	10.06	2.90	0.61	1605.43	0.03	0.43	8.26	8	1.40	2.79	15.32
F11-03	6.48	2.53	0.45	1033.25	0.01	0.26	2.48	5	1.03	2.07	6.80
F11-04	9.44	2.71	0.61	1505.09	0.02	0.43	6.81	7	1.21	2.43	12.28
F11-05	6.01	2.35	0.45	959.44	0.01	0.26	1.99	4	0.85	1.71	5.06
F11-06	10.98	2.71	0.70	1751.38	0.03	0.55	10.19	8	1.21	2.43	15.07
F11-07	10.00	2.90	0.60	1594.81	0.03	0.42	8.12	7	1.40	2.79	14.49
Total	64.3	18.91		10256.58	0.15		49.05	47	8.41	16.83	85.51

Table 3. TL estimation result of case study B

11kV feeder number	Length (km)	Estimated MD(MW)	LF	Infeed Energy (MWh/month)	PPL base (MW)	LsF	Feeder losses (MWh)	No of tx.	Power (MW)	TCF	Tx. losses (MWh)
F11-01	7.51	5.34	0.70	4009.65	0.05	0.55	18.83	9	2.34	4.68	40.93
F11-02	6.35	5.25	0.61	3392.21	0.04	0.43	11.99	8	2.25	4.50	30.57
F11-03	4.59	5.16	0.45	2452.08	0.03	0.26	5.11	5	2.16	4.32	17.54
F11-04	6.46	5.34	0.61	3450.69	0.04	0.43	12.63	8	2.34	4.68	32.61
F11-05	4.75	5.34	0.45	2538.11	0.03	0.26	5.67	6	2.34	4.68	20.70
F11-06	7.14	5.07	0.70	3811.18	0.04	0.55	16.16	9	2.07	4.14	33.46
F11-07	6.53	5.43	0.60	3485.98	0.04	0.42	13.05	8	2.43	4.86	34.41
F11-08	7.41	5.25	0.71	3952.90	0.05	0.55	18.02	9	2.25	4.50	38.47
Total	50.75	42.17		27092.79	0.32		101.46	62	18.17	36.35	248.69

Note: MD=maximum demand; LF=load factor; PPL=peak power loss; LsF=loss factor; Tx.= transformer; TCF=transformer capacity factor

Beyond cable length, LF and LsF significantly influence distribution losses. Densely populated areas with higher LFs often experience increased energy demand, which translates into higher losses, as depicted in Figures 5(b) and 6(b). This observation resonates with previous findings [24], [25], though it is important to note that LF alone is not always a reliable predictor. For instance, some areas with high LF do not necessarily show proportionally high losses, indicating the presence of other influencing variables. Meanwhile, LsF which reflects overall system efficiency, presents a more consistent indicator of system performance. As shown in Figures 5(c) and 6(c), a lower LsF generally correlates with reduced energy losses, supporting claims in [26], [27] regarding the value of optimized network design. Recent studies further support this, showing that while higher LF typically corresponds with lower TL due to steadier load profiles, it is the LsF that more accurately captures the impact of load variability on losses. Research findings [28], [29] confirm that systems with high LsF exhibit significantly greater energy losses, primarily due to peak-induced I^2R effects. Thus, minimizing LsF through load management strategies proves crucial for loss reduction and efficient distribution network performance.

However, an unexpected outcome emerged in the analysis of losses against transformer capacity factor. While theory suggests that higher capacity utilization should result in improved efficiency and reduced losses [30], [31], the data from case study A (Figure 5(d)) reveals higher losses even at elevated transformer capacity factors. Meanwhile, the pattern in case study B (Figure 6(d)) appears scattered and inconsistent. Therefore, it is apparent that the transformer capacity factor may not hold the primary influence on the observed losses. Instead, factors such as load profiles, network topologies, or even aging infrastructure, seem to carry more substantial weight which have been proven by authors in [32]. These insights mirror findings in [33] where the author presented an optimization approach to minimize power losses in distribution networks and suggest a more nuanced interpretation of power efficiency.

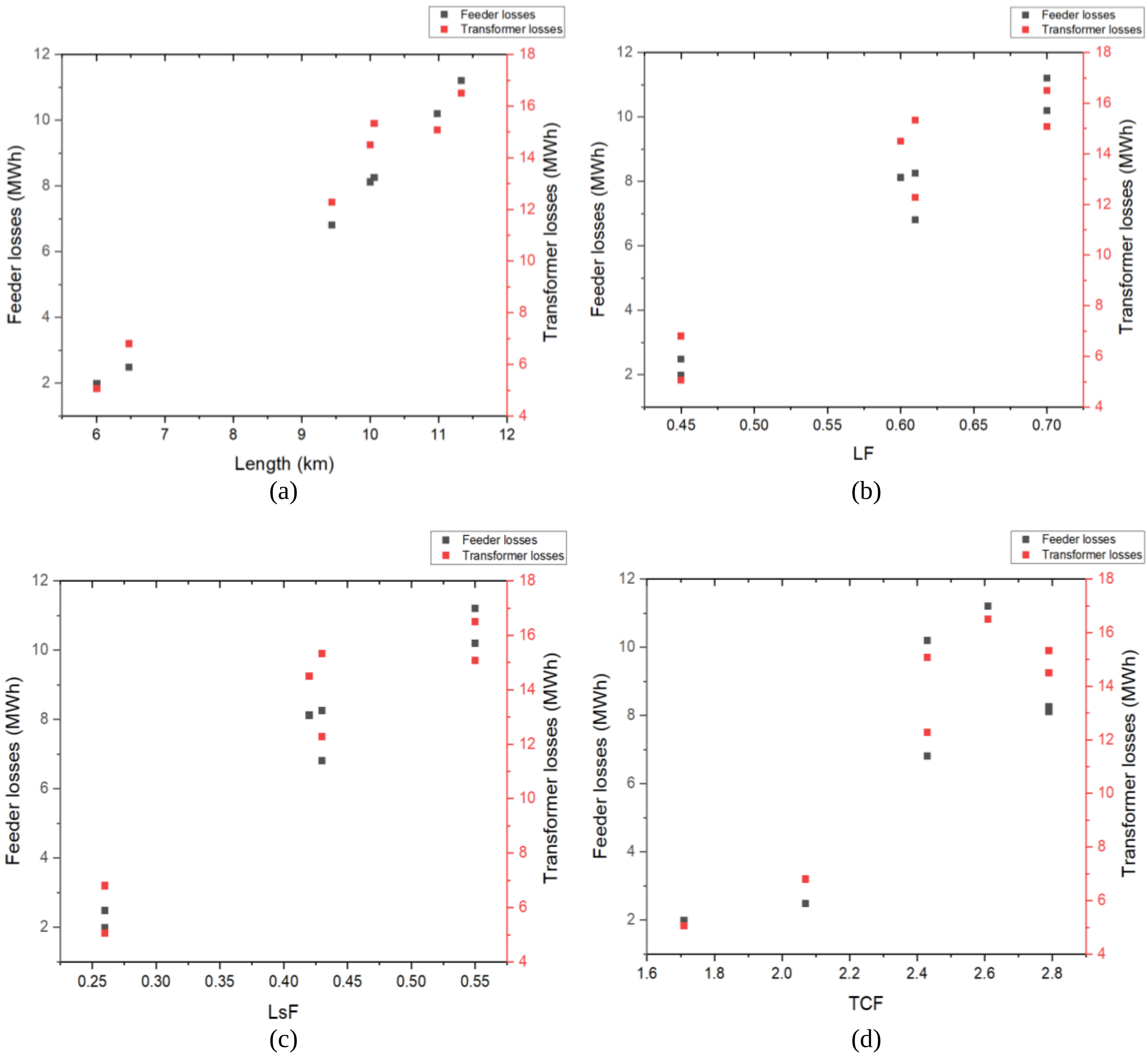

Figure 5. Graphs of losses against (a) length, (b) LF, (c) LsF, and (d) TCF for case study A

Overall, cable length exhibits a more linear and intuitive relationship with TL in both case studies. This supports the established understanding that conductor resistance and energy dissipation scale with length and load current, in accordance with Joule's law [34]. This also suggests that network reconfiguration or conductor upgrading can be effective loss mitigation strategies. The LsF, a composite indicator considering average and peak load, presents a more consistent correlation with TL. This demonstrates the effectiveness of LsF in capturing load variability and its resultant impact on energy losses. Utilities may benefit from incorporating LsF-based estimations in daily planning routines to better target high-loss feeders.

Mitigating energy losses necessitates addressing both feeder and transformer losses. Optimizing transformer capacity factor, cable lengths, LF, and LsF represents an interconnected set of strategies for minimizing energy losses in a distribution system [35]-[37]. A comprehensive approach that takes into account the interplay of these factors is indispensable for achieving an energy-efficient and sustainable electrical infrastructure. This could entail enhancements such as upgrading conductors, refining transformer designs, and incorporating energy-efficient technologies. Therefore, strategies for mitigation should encompass the optimization of both feeders and transformers to effectively minimize overall energy losses.

Table 4 depicts the result of total energy losses, carbon footprint, and cost rates for both case studies A and B. The inefficiencies in energy transmission resulting from distribution losses in an electrical power system contribute to elevated carbon emissions. When electricity is lost during distribution, additional energy must be generated to meet demand, often from sources associated with GHG emissions [38]. Consequently, feeder F11-01 exhibits the highest carbon footprint due to its elevated total energy losses. Specifically, in case study A, feeder F11-01 registers the highest losses at 27.69 MWh, resulting in a carbon footprint of 17.69. Similarly, in case study B, feeder F11-01 records the highest losses at 59.76 MWh, corresponding to the highest carbon footprint of 38.19.

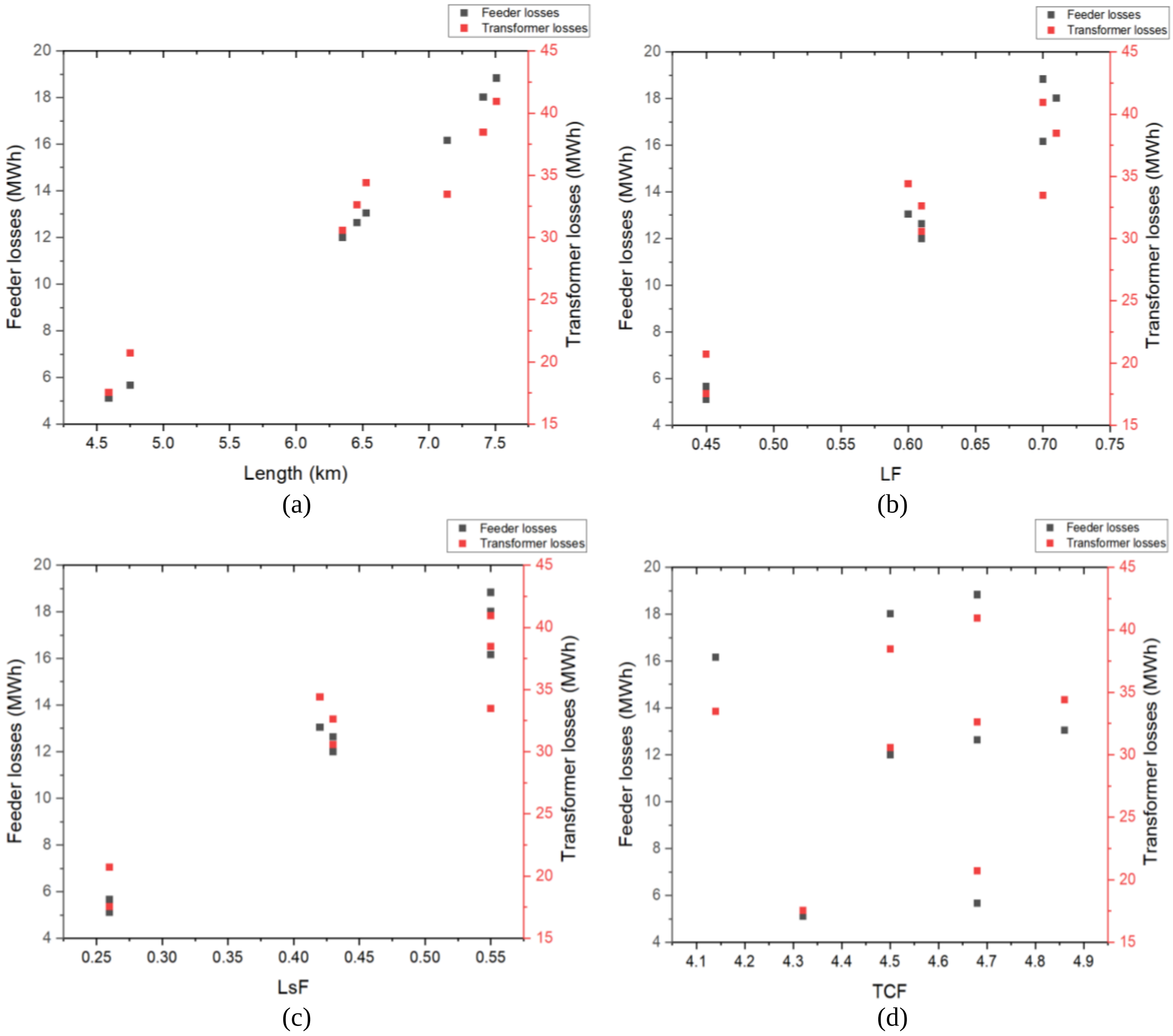

Figure 6. Graphs of losses against (a) length, (b) LF, (c) LsF, and (d) TCF for case study B

Therefore, the direct reduction of distribution losses plays a pivotal role in lowering the carbon footprint of the energy distribution process [39], as observed in feeder F11-03 for both case studies. This impact is contingent on the energy mix utilized for electricity generation, where a substantial reliance on fossil fuels with high emission intensity amplifies the carbon footprint associated with distribution losses [40]. The composition of electricity generation sources in Malaysia is predominantly fueled by natural gas, with coal and oil also contributing significantly [41]. The combustion of fossil fuels results in the emission of carbon dioxide. Conversely, if the energy is predominantly sourced from low-emission or renewable sources, the impact on the carbon footprint is less severe.

Distribution losses also have economic implications. The energy lost during distribution represents a financial cost to utilities because more energy must be generated to compensate for these losses. Table 4 illustrates that the cost rates at F11-01 for case study A are higher, at RM/MWh 6.15, and similarly in case study B at RM/MWh 13.27, reflecting their respective highest total energy losses. This higher generation involves expenses related to fuel, maintenance, and operational costs, impacting the economic viability of the power distribution system [42]. This analysis aids in pinpointing areas of substantial expenditure and potential opportunities for cost reduction. Therefore, evaluating the costs linked to distribution losses necessitates considering both the financial outlays resulting from increased energy generation and the environmental costs associated with carbon emissions which have been emphasized by author in [43].

Table 4. Energy losses estimation with its respective carbon footprint and cost rates

11kV feeder number	Case study A			Case study B		
	Total energy losses (MWh)	Carbon footprint	Rates (RM/MWh)	Total energy losses (MWh)	Carbon footprint	Rates (RM/MWh)
F11-01	27.69	17.69	6.15	59.76	38.19	13.27
F11-02	23.58	15.07	5.52	42.56	27.20	9.96
F11-03	9.28	5.93	2.86	22.65	14.47	7.03
F11-04	19.09	12.20	4.47	45.23	28.90	10.58
F11-05	7.04	4.50	2.16	26.37	16.85	8.19
F11-06	25.26	16.14	5.61	49.62	31.71	11.02
F11-07	22.62	14.45	5.29	47.46	30.33	11.11
F11-08	-	-	-	56.49	36.10	12.54
	134.57	85.99	32.05	350.15	223.74	83.69

This study demonstrates that the proposed estimation approach effectively captures key variables affecting TL in power distribution. Cable length, LF, LsF, and transformer capacity factor interact in complex ways, but their analysis enables better-informed strategies for loss reduction. Effectively managing and reducing distribution losses can offer long-term economic benefits [44]. While there might be initial costs associated with implementing these measures, the long-term advantages include reduced carbon emissions, diminished operational costs, and heightened overall system efficiency. Numerous countries and regions have established regulatory frameworks or policies that provide incentives for utilities to minimize distribution losses, aligning with broader sustainability objectives. Adherence to these regulations can affect both the carbon footprint and the economic costs linked to distribution losses. Initiatives focused on mitigating these losses not only foster environmental sustainability through reduced carbon emissions but also yield economic advantages by enhancing energy utilization and operational efficiency.

4. CONCLUSION

Minimizing losses in both feeder and transformer networks is essential for cost savings and reducing GHG emissions in the distribution system. This study demonstrates that while accurate loss estimation in large and complex networks typically requires detailed data and computationally intensive processes, practical solutions are possible even with limited resources. By applying a simplified analytical approach based on energy distribution equations and historical load profiles, this research provides a feasible and scalable method for estimating TL across different feeder and transformer configurations.

The study’s findings reveal consistent and interpretable patterns in losses across various case studies for feeder sections and transformer losses, highlighting the robustness and applicability of the proposed methodology. These results contribute to real-world applications by offering utilities a practical tool for identifying high-loss segments and improving operational efficiency. Importantly, the integration of realistic sector-based tariffs further enhances the economic and policy relevance of the outcomes. In alignment with the GESS framework, this research underscores the broader implications of loss estimation as a foundation for environmentally responsible and economically viable energy strategies. It also reflects the evolving responsibilities of modern utilities to balance performance, regulatory compliance, and sustainability.

Looking forward, the study highlights the potential for enhancing this methodology through the integration of multi-variable models, advanced analytics, and explainable AI. Such approaches could offer greater accuracy, insight, and transparency, particularly in the face of increasing data availability and system complexity. These advancements could empower utilities, policymakers, and researchers alike to make more informed, data-driven decisions in designing resilient and low-loss distribution networks. Overall, the findings establish groundwork for future studies and the implementation of strategies aligned with GESS principles, aiming to create solutions with both environmental and economic benefits.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article.

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