

Stray Load Losses Estimation in Three-phase Induction Motors Using a Non-invasive Multilayer Perceptron Neural Network-based Model

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Abstract—In operating induction motors (IMs), accurately estimating stray load losses (SLLs) through non-invasive techniques is essential to avoid performance disruptions. Due to the high complexity and invasiveness of direct measurement, as well as its impossibility in certain applications, empirical relationships are commonly used to estimate SLL. This paper introduces a novel model for estimating SLL in low-voltage, three-phase IMs using data from 425 simulated IMs in MATLAB, covering 380 V, 50 Hz IMs with different pole numbers and power ratings from 0.37 to 400 kW. SLL values were computed according to method B in the IEEE 112 standard. The novelty of this research lies in, for the first time, employing a multilayer perceptron neural network as a non-intrusive machine learning (ML) approach to estimate SLL using IM nameplate data, input power, and total harmonic distortion (THD). The developed model exhibits a strong correlation with simulated data, enabling accurate predictions under diverse operating conditions without requiring physical access to motor internals. Its effectiveness was confirmed through simulations and experimental validation, highlighting its potential as a precise and fully non-invasive method for estimating SLL in IMs.

Index Terms—IEC 60034-2-1 standard, IEEE 112 standard, Induction motor (IM), Multilayer perceptron (MLP), Stray load losses (SLLs), Total harmonic distortion (THD).

I. INTRODUCTION

DUE to their efficiency, durability, and reliability, induction motors (IMs) are a popular choice for various applications, including those in industrial, commercial, and electric vehicle settings. Precise parameter estimation and monitoring are vital for efficient IM operation and loss reduction [1]. Losses, classified by IEEE/IEC standards, encompass iron, copper, mechanical, and stray load losses

(SLLs) [2]–[3]. In IMs, SLL is a function of the air gap flux density, the level of harmonic components present in the current and voltage, and the precise design of the stator and rotor slots [4]. Structural inhomogeneities, the motor's load level, supply frequency and voltage, and even the motor's overall design, including the length-to-diameter ratio, all contribute to the magnitude of these losses [5].

Methods for determining SLL fall into three categories: standard-based, finite element analysis (FEA), and SLL estimation methods. Standards-based approaches utilize international standards, such as IEEE 112 and IEC 60034-2-1, for SLL assessment. FEA methods, encompassing two-dimensional (2D) and three-dimensional (3D) simulations, offer more accurate SLL evaluation through modeling software. SLL estimation methods are further divided into empirical relationship methods, which rely on experimental data, and equivalent circuit (EC) methods, which employ EC models for SLL calculation. Each category provides distinct tools for SLL determination [3].

The SLL measurement in IMs is performed based on various standards; however, these standards often yield different results and have limited accuracy. The main challenge is the precise separation of SLL from other IM losses, as SLL is usually not directly measurable and depends on loading conditions [6]. Due to the invasive nature of measuring SLL in various standards, non-invasive empirical relations have been developed for calculating SLL. Here, invasive methods refer to procedures requiring physical intervention that disturbs the motor's normal operating state, such as stopping the motor and decoupling the load, disassembling motor's components, or inserting additional sensors. Based on [7], a comparison of standards such as IEEE 112-B, IEC 60034-2-1, and JEC 37 reveals that the precise calculation of SLL is essential for correct efficiency calculations.

SLL can be determined via 2D/3D FEA or the IM's EC. While FEA, particularly 3D, offers high accuracy by detailing electromagnetic fields and losses, it is computationally intensive. The EC method provides a faster, simpler estimation; however, accurately determining its parameters is challenging. This reliance on approximations makes the EC method less precise than FEA, especially for IMs with varied operating conditions or complex designs [8]–[9]. In [10],

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comparing methods like FEA, genetic algorithms (GAs), and empirical approaches for IM loss estimation, including SLL, shows FEA to be more accurate. In [11], FEA was integrated with experimental data to enhance SLL estimation. The impact of harmonics on SLL and efficiency was investigated in [12]. Furthermore, [13] introduced updated algorithms for evaluating repaired IM efficiency, which improved accuracy by estimating SLL using these EC-based algorithms.

Several advanced techniques refine SLL calculations in IMs. For instance, [14] introduces a hybrid approach combining generalized airgap flux modulation theory with 2D FEA, enabling designers to optimize IM efficiency without physical prototypes. In [15], associated leakage currents and SLLs were examined, enhancing EC models with resistance-based formulas for precise efficiency assessment. An empirical model for SLL calculation in inverter-fed IMs, developed in [5], achieved high accuracy across diverse test points. ECs for computation of mechanical and SLL losses were explored in [16], demonstrating improved loss distribution accuracy via nonlinear programming. The influence of sinusoidal supply voltage variations on SLL was modeled in [17], while space harmonics in squirrel cage IMs were addressed through additional resistance methods in [18].

Empirical relations estimate SLL in IMs using formulas derived from experimental data, linking SLL to parameters like rated input power and empirical coefficients. While providing quick and simple initial estimates, accuracy depends on the original experimental conditions. This method may fail under different conditions and often misses complex motor design details [19]. A formula for SLL estimation in IMs was validated against the IEEE 112 standard in [20], offering higher precision than the standard.

Given the intrusive nature of SLL measurement based on standards, the use of empirical relations provided in these standards is preferred for determining SLL in IMs. The EC method, despite its high accuracy, is also intrusive and requires the determination of the EC parameters. FEA-based SLL calculation is limited by its dependence on IM material data, computational demands, and modeling complexities. In addition to the empirical relations in standards, some non-invasive empirical approaches exist for SLL estimation, though their accuracy remains questionable. As a result, a non-invasive model with acceptable accuracy is needed to determine SLL in IMs.

In the literature, machine learning (ML) has not been applied to estimate SLL in IMs. This article introduces a non-invasive model based on the multilayer perceptron (MLP) neural network to overcome challenges in SLL estimation. The novelty of this research lies in employing the MLP for non-invasive SLL estimation in operating IMs utilizing only accessible data. MLP was selected for its superior nonlinear mapping, strong function approximation, and higher flexibility compared to decision trees, random forest, and regression models. The model was trained using data obtained from simulations of 425 IMs with varying power ratings (0.37-400 kW) conducted in MATLAB software with publicly available manufacturer data. SLL values were

calculated under method B of IEEE 112. The proposed model non-invasively accurately estimates SLL across diverse operating conditions using nameplate data, input power, and total harmonic distortion (THD). It captures the effect of supply harmonics in both inverter-fed and line-fed IMs, supporting non-invasive SLL estimation and IM design applications.

The effectiveness of the proposed model is rigorously validated through simulation and experimentation. The simulation validation involves comparing SLL estimations using the proposed model with those obtained from empirical relations. The experimental validation involves comparing SLL estimations using the suggested model with measurements from experimental setups and calculations based on existing empirical relations. Both the simulation and experimental results demonstrate the accuracy of the proposed model in estimating SLL.

The remaining sections of this paper are structured as follows: Section II reviews the methods used to determine SLL in IMs. Section III introduces the proposed model for estimating the SLL. Section IV presents and analyzes the simulation results. Section V describes the experimental setup and shares the corresponding findings. Section VI discusses the limitations and applications of the proposed model. Finally, Section VII offers a conclusion about the study.

II. SLL DETERMINATION METHODS IN IMs

Various methods exist for computing SLL in IMs. Each offers a unique approach to calculation. These SLL calculation procedures are detailed separately below.

A. SLL Measurement Using Standards

Standards, such as IEC 60034-2-1, IEEE 112, JEC 37, and NEMA MG1, propose different methods for calculating SLL in IMs, yielding varying results for these losses. In method B of IEEE 112, SLL is calculated by subtracting ohmic, iron, and mechanical losses from the total IM losses, as shown in (1). Conversely, methods E and F estimate SLL based on the reverse rotation and the removed rotor tests [21].

$$P_{\text{sll}} = (P_i - P_o) - (P_{\text{ohmic},s} + P_{\text{ohmic},r} + P_{\text{iron}} + P_{\text{fw}}) \quad (1)$$

where P_{sll} is the SLL; P_i is the IM input power; P_o is the IM output power; $P_{\text{ohmic},s}$ and $P_{\text{ohmic},r}$ are the stator and rotor ohmic losses; P_{iron} is the iron loss; P_{fw} is the mechanical loss.

The no-load test determines iron and mechanical losses. Stator copper losses are calculated using the stator resistance and operating current values, and the rotor copper losses are computed using the slip and airgap power at the operating point. Based on methods E and F in the IEEE 112 standard, in the removed rotor test, the IM rotor is removed, and the stator's power, voltage, current, and resistance are measured to calculate the SLL at fundamental frequency. In the reverse rotation test, the stator is connected to the power supply, and the rotor is rotated at synchronous speed in the opposite direction, resulting in high-frequency losses. (2) and (3) express the components of SLL at fundamental ($P_{\text{sll},f}$) and high frequencies ($P_{\text{sll},hf}$) based on input power, necessary

mechanical power, and stator copper loss. The sum of these components indicates the SLL [21].

$$P_{sll,f} = P_{i,f} - 3R_s I_s^2 \quad (2)$$

$$P_{sll,hf} = (P_{mech} - P_m) - (P_{rev} - P_{i,f} - P_{cu,rev}) \quad (3)$$

where $P_{i,f}$ is the input power in the removed rotor test; P_{mech} is the mechanical power required to move the rotor by applying voltage to the stator; P_m is the mechanical power necessary to move the rotor without applying voltage to the stator; P_{rev} is the electrical power input to the stator windings during the reverse rotation test; $P_{cu,rev}$ is the stator copper loss in the reverse rotation test [3], [21]. Measurement of SLL in operating IMs, as per methods B, E, and F in the IEEE 112 standard, is highly invasive and often not feasible. Therefore, for determining SLL, the empirical approach presented in method E1 of IEEE 112 is utilized. In this method, SLL at rated load is expressed as a percentage of the IM's rated output power ($P_{o,r}$), according to the values provided in Table I. For other load points, SLL losses are considered proportional to the square of the rotor current and are calculated using (4) [3]:

$$P_{sll,p} = P_{sll,r} \left(\frac{I_s^2 - I_{nl}^2}{I_{rot,r}^2} \right) \quad (4)$$

where $P_{sll,p}$ is the SLL in the specified load point; $P_{sll,r}$ is the SLL at the rated load; I_s is the stator current in the specified load point; I_{nl} is the no-load current; $I_{rot,r}$ is the rotor current at the rated load.

TABLE I
ASSUMED SLL VALUE BASED ON METHOD E1 OF IEEE 112
STANDARD [3], [21]

$P_{o,r}$	SLL value as a percentage of $P_{o,r}$
125 hp and below	1.8%
126-500 hp	1.5%
501-2499 hp	1.2%
2500 hp and above	0.9%

According to the IEEE 112 standard, methods E and F (removed rotor, reverse rotation) and method B (loss segregation) are invasive. They interrupt normal motor operation, requiring a stop, load decoupling, rotor removal, or reverse driving. These actions impose abnormal mechanical/electrical stress and demand direct terminal access, interfering with the supply or drive circuitry. Hence, they are impractical for in-service IMs and limited to laboratories.

In the IEC 60034 standard, the SLL value is assumed to be 0.5% of the IM's rated output power. Due to the low accuracy of this value, this method has been modified in the new version, IEC 60034-2-1. In the IEC 60034-2-1 standard, the SLL value is estimated using empirical relations based on the IM's rated input and output power, as shown in (5) [3], [22]:

$$P_{sll} = \begin{cases} 0.025P_i & P_{o,r} < 1 \text{ kW} \\ P_i \left(0.025 - 0.005 \log_{10} \left(\frac{P_{o,r}}{1 \text{ kW}} \right) \right) & 1 \text{ kW} < P_{o,r} < 10 \text{ MW} \\ 0.005P_i & P_{o,r} > 10 \text{ MW} \end{cases} \quad (5)$$

The JEC37 standard has lower accuracy in SLL evaluation compared to the IEEE 112 and IEC 60034-2-1 standards. It assumes SLL is negligible ($P_{sll} = 0$) [3], [23]. NEMA MG1 standard provides measurement techniques via tests and theoretical computations, mirroring methods E and F in IEEE 112. If direct measurement is infeasible, SLL is expressed as a percentage of the $P_{o,r}$, as shown in Table II [3], [24].

Specifying SLL based on empirical relations in standards, while facile and accessible, comes with certain limitations. One of the most significant challenges is the discrepancy in the assumed values of SLL across different standards. These differences, particularly in industrial applications where accuracy is crucial, diminish trust in these methods.

TABLE II
ASSUMED SLL VALUE BASED ON NEMA-MG1 STANDARD [3], [24]

$P_{o,r}$	SLL value as a percentage of $P_{o,r}$
2499 hp and below	1.2%
2500 hp and above	0.9%

B. SLL Calculation Using FEA-based Techniques

Beyond standard practices, recent studies highlight the use of FEA for more precise SLL estimation in IMs. This approach utilizes specialized software to develop detailed motor models that simulate electromagnetic behavior by defining geometry, material properties, and operating conditions for accurate 2D or 3D representations. FEA enables numerical calculation of SLL, offering valuable insights into motor performance [3]. However, its practical application is limited by the requirement for detailed design data, magnetic material properties, and geometric details that are often unavailable for in-service IMs. Hence, FEA is typically used in laboratory settings or under carefully controlled conditions.

C. SLL Estimation Using Empirical Relations

In this approach, after conducting various tests on a set of IMs and analyzing the results, relations are derived for calculating SLL. An empirical formula for estimating SLL, derived from extensive testing of 182 IMs at various power levels, is presented in [20]. This formula shows greater accuracy compared to standard-based methods and is specified in (6). One limitation of this relation is that it considers SLL solely as a function of input power, neglecting other factors such as IM dimensions and slot arrangement. Thus, empirical methods, though simple and relatively precise, fail when motors with identical power but different geometries exhibit varied leakage flux and, hence, different SLL values [3].

$$P_{sll} = 0.0011P_i \quad (6)$$

D. SLL Determination Using IM Equivalent Circuit

Intelligent algorithms (IAs) offer an accurate estimation of EC parameters of IM, supplementing traditional laboratory methods. Precise EC parameter values enable the calculation of SLL across various IM operating conditions. A proposed EC for computing SLL in IMs, shown in Fig. 1, incorporates a series resistance (R_{sll}) representing SLL, connected in series

with the X_{lr} . Key parameters of the EC, including X_{ls} , X_g , R_r , and R_i , are determined by IA-based approaches. The parameters X_{lr} , X_{ls} , X_g , R_r , and R_i represent the rotor leakage reactance, stator leakage reactance, magnetizing reactance, rotor resistance, and iron-loss resistance, respectively. The NEMA-MG1 standard, in Table III [24], defines the relationship between X_{ls} and X_{lr} . After estimating the parameters X_{ls} , X_g , R_r , and R_i , the X_{lr} value is calculated according to Table III. R_s is either measured or estimated. Ultimately, R_{still} , signifying SLL, is computed using (7) [25].

$$R_{still} = \frac{0.018R_r(1-S_{fl})}{S_{fl}} \quad (7)$$

where S_{fl} is the slip in full load. The potentially invasive aspect of the EC method does not stem from equipment interference, but rather from the necessity of performing specialized offline tests, like the no-load and locked-rotor tests, which inherently alter the IM's operational state. This invasiveness is then amplified by the significant data requirements and integration complexities associated with the IA themselves, as they necessitate controlled interventions to produce accurate SLL estimations. Consequently, the identification of EC parameters through IAs within EC methods can be seen as invasive, making their application for determining SLL in operational IMs a less favorable choice.

TABLE III
RATIO BETWEEN X_{ls} AND X_{lr} IN NEMA MG1 STANDARD [24]

Design class	X_{ls}/X_{lr} ratio
A	1.00
B	0.67
C	0.43
D	1.00

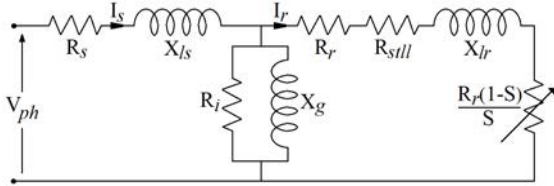


Fig. 1. Proposed EC for analyzing SLL in three-phase IMs [3].

III. PROPOSED MODEL FOR ESTIMATING SLL

This section outlines the methodology behind the proposed model for estimating SLL in IMs. The model was developed based on data acquired from calculating SLL in 425 simulated IMs in MATLAB software. The 425 simulated IMs were modeled using data from several manufacturers, covering efficiency classes IE1 to IE3, both squirrel-cage and wound-rotor types, and a wide range of rated powers and pole numbers; their basic specifications are given in Table IV [1]. Cage materials vary from aluminum (low/medium power) to copper (high power). Different frame sizes and multiple designs per power level ensure substantial diversity, reducing the risk of overfitting to any specific motor family.

The simulated IMs dynamically adjust electrical parameters with load to reflect nonlinear effects such as magnetic saturation and conductor losses, achieving realistic motor behavior. Final results were validated against manufacturer

data to ensure model accuracy. To ensure a comparative validation of the simulated IMs against physical IMs in catalogs, four distinct IMs were selected, varying in pole count and power ratings. These selected motors were then operated under their rated load conditions. Key operational parameters, such as current, torque, and efficiency, were measured for both the physical IMs and their simulated counterparts. Table V presents a detailed comparison of these parameters. The observed exact agreement between the simulated and physical motor parameters unequivocally demonstrates that the developed simulation IMs accurately replicate the dynamic behavior of real-world IMs.

TABLE IV
THE INFORMATION ON THE STUDIED IMs

Simulated IMs data				
	Number of IMs	Fed voltage/V	Frequency/Hz	Nominal output power range/kW
2-pole	113	380	50	0.37 to 400
4-pole	113	380	50	0.37 to 400
6-pole	106	380	50	0.37 to 315
8-pole	93	380	50	0.37 to 250

TABLE V
KEY OPERATING PARAMETERS AT FULL LOAD FOR
SIMULATED AND PHYSICAL IMs

Parameter		IM 1 (4-pole)	IM 2 (8-pole)	IM 3 (2-pole)	IM 4 (6-pole)
Simulated	Input power/kW	48.911	116.649	16.573	80.128
		48.910	116.648	16.574	80.13
Simulated	Efficiency/%	92	94.3	90.5	93.6
		92	94.3	90.5	93.6
Simulated	Rated current/A	85.42	211.01	28.29	141.59
		85.4	211	28.3	141.6
Simulated	Rated speed/(r/min)	1465	743	2955	983
		1465	743	2955	983
Simulated	Torque/(N·m)	293.31	1413.8	48.474	728.58
		293.3	1413.8	48.47	728.6
Simulated	Output power/kW	45	110	15	75
		45	110	15	75

The SLL estimation model was developed using the MLP algorithm, trained on data obtained by calculating SLL in simulated IMs under various operating conditions, based on method B in IEEE standard 112. ML-based approaches have not been applied to SLL estimation in IMs. MLP was chosen for its strong function approximation and higher flexibility compared to other ML algorithms. Hence, the superiority of the suggested MLP model is non-invasive SLL prediction using accessible data. Next, the MLP algorithm, its execution, and the proposed model development stages will be described.

The MLP is a foundational artificial neural network architecture adept at learning intricate, non-linear data relationships. Featuring an input layer, multiple hidden layers, and an output layer, its neurons process information through interconnected pathways. MLPs learn via backpropagation, an iterative technique where connection weights are adjusted to minimize prediction errors against target values. By propagating errors backward and updating these weights, MLPs excel at modeling complex patterns, rendering them highly versatile for a multitude of applications across various domains. This capability to decipher intricate relations

through layered processing and error-driven adjustments is key to their extensive utility [26].

MLPs distinguish themselves through an iterative error correction mechanism, setting them apart from ensemble methods. Parameters like layer structure and learning rate are configured before a forward pass generates an initial output. This output is then compared with actual targets, and an error is calculated. The backpropagation algorithm efficiently propagates this error backward, adjusting neuron connection weights to minimize discrepancies. This forward prediction and backward error correction cycle iteratively refines the network's mapping, enhancing its ability to learn complex relations and making it a powerful tool for power engineering tasks such as fault diagnosis and system modeling [26].

Initially, a baseline model was established using calculated SLL for IMs in full load at 50 Hz, balanced and harmonic-free supply conditions. Following method B of IEEE Standard 112, total losses were derived by subtracting P_o from P_i . Ohmic losses at full load were calculated, and mechanical and iron losses were calculated via a no-load test. SLL was then determined by subtracting ohmic, iron, and mechanical losses from the total losses. Subsequently, an initial SLL prediction model for IMs was developed employing the MLP algorithm. In this process, data regarding output power, input power, and SLL values for each motor were stored separately. The input power at rated load was considered an independent variable, and the initial model was built based on this parameter.

The initial MLP model estimates SLL in IMs using nominal full-load data at 50 Hz without harmonics. However, a significant limitation was its inability to incorporate load variations, despite SLL being load-dependent. To overcome this, new datasets were created through simulations conducted across various load points (40% to 120% of rated load) at 50 Hz. These expanded datasets were subsequently used to retrain the model, thereby enhancing its accuracy in capturing the intricate relation between SLL and diverse load conditions.

In practical scenarios, especially with inverter-fed IMs, harmonic components are present in the supply voltage, directly influencing SLL. To address this, SLL was calculated for simulated IMs across 0-20% THD levels (in 5% steps). This THD value was subsequently incorporated as a new input to the model. While carrier frequency and modulation methods also influence SLL by affecting THD, the proposed model implicitly accounts for these factors through the THD input, as it serves as a key indicator of the supply's harmonic content. The model was then retrained, resulting in a final version capable of accurately estimating SLL at various load points and under supply conditions with harmonic content.

The final trained model was developed using the MLP. This choice was driven by the MLP's capability to model the intricate, non-linear dependencies essential for SLL estimation, outperforming regression and simpler ML techniques. The model integrated diverse input data, encompassing input power, THD, and nameplate data, ensuring comprehensive coverage of operational conditions. The MLP architecture featured two hidden layers employing

"tansig" transfer functions. The first layer's neuron count was optimized, ranging between 30 and 45 neurons, with the second layer featuring five fewer neurons. Training utilized the "trainlm" (Levenberg-Marquardt) algorithm for up to 1000 epochs, incorporating an early stopping mechanism (30 epochs without validation improvement) and key parameters: a learning rate of 0.0003 and a decay rate of 0.995. These hyperparameters were determined through an iterative empirical tuning process to ensure stable convergence and an optimal balance between training speed and model accuracy.

To enhance accuracy, especially for high-output power samples, and to ensure robust generalization while preventing overfitting, a two-phase weighting strategy was implemented. This involved initial weighting based on the inverse of the kernel density estimation of the rated output power, followed by a final training phase that prioritized samples with higher initial prediction errors. This holistic methodology ensures the MLP-based model's ability to generalize across various operational states and mitigate overfitting, delivering precise SLL estimates essential for practical applications.

While approaches like method B of IEEE 112 standard have limitations in loss separation, the lack of proprietary geometric data for FEM analysis necessitated an extensive MATLAB simulation of 425 IMs. By validating these models against catalog specifications, the MLP was trained to learn underlying physical relationships rather than memorizing raw data. This approach effectively mitigates measurement noise and enhances the model's generalization capabilities.

Fig. 2 shows the progression of the mean squared error (MSE) over the epochs during the training process. The graph clearly illustrates how the error steadily decreases as training progresses, indicating that the model is effectively learning and adjusting its weights. The convergence of the MSE curve suggests that the model has reached a stable state, where further training does not result in significant improvements in accuracy. This behavior confirms that the training process was successful and that the model has achieved excellent convergence performance. Additionally, no signs of overfitting are observed, meaning that the model generalizes well to unseen data and maintains robustness across various operational scenarios.

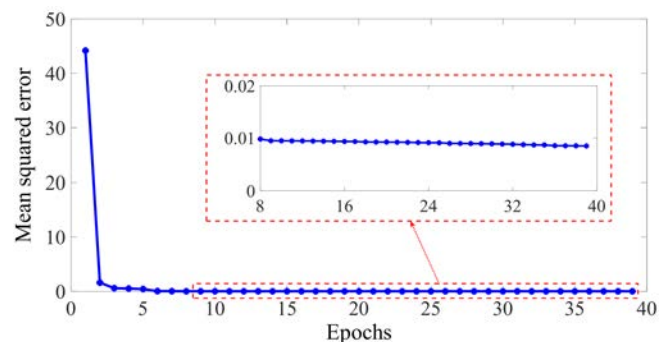


Fig. 2. Progression of the MSE over the epochs during the training process of the model.

Following the final training of the model based on the extracted data from 425 simulated IMs within MATLAB, the trained model is used to estimate the SLL in new IMs,

specifically, those not included in the 425 simulated IMs. To facilitate this, a prediction code has been developed that estimates the SLL for each new IM based on the recorded data of the trained model and using the data of the IM under study (including the information on the IM nameplate, input power, and THD values). If the new IM's data match the trained model's registered dataset, the SLL is estimated directly based on the registered data. Otherwise, if the new IM data does not correspond with the registered dataset in the trained model, the prediction code considers the closest relevant values from the registered information of the trained model and estimates the SLL of the IM in question using nonlinear interpolation. The flowchart of the proposed model implementation process for non-invasive SLL estimation is shown in Fig. 3.

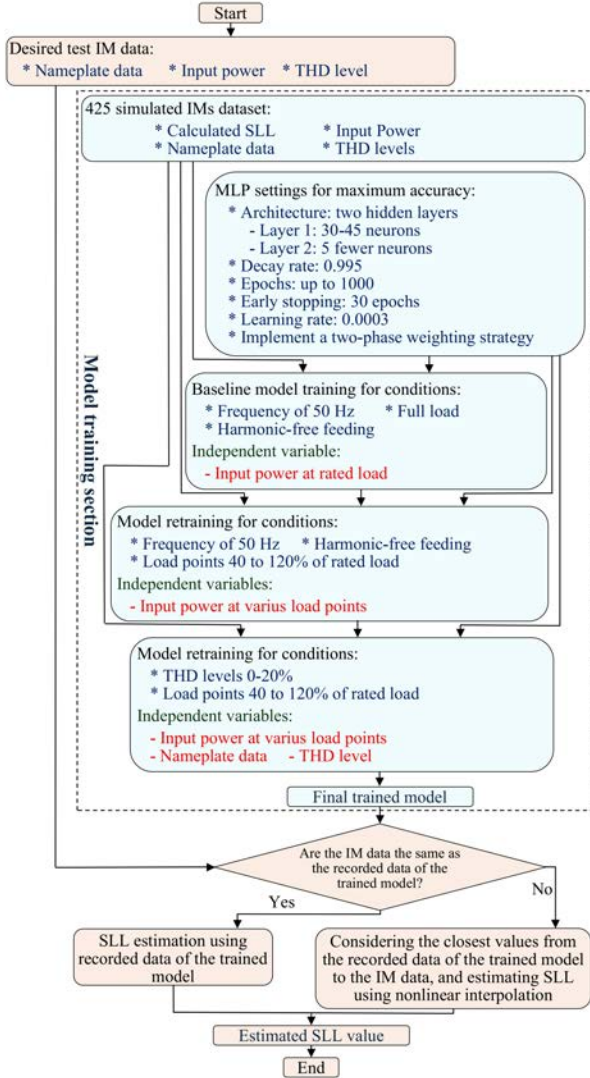


Fig. 3. The flowchart of the proposed model implementation process.

The proposed model for accurately estimating SLL in each IM requires only IM nameplate data, input power, and THD values, which makes the proposed model non-invasive. While certain IM design factors, such as different geometric structures, do influence SLL, their effects are implicitly incorporated into the model's training process due to the adequate variability within the simulated motors.

Consequently, their contribution to the final model's error is minimal, especially in industrial applications. Therefore, the proposed model emerges as a simpler and much more efficient alternative compared to invasive methods for estimating SLL.

IV. SIMULATION RESULTS, DISCUSSION, AND COMPARISONS

This section is organized into two subsections: a) proposed model performance evaluation on test data, and b) physical response validation. The first subsection presents a comparative accuracy analysis, whereas the second investigates the physical consistency of the proposed model's behavior through response-sensitivity examination.

A. Comparative Accuracy Evaluation on Simulated Data

In this subsection, the accuracy of the proposed SLL estimation model is investigated based on the analysis of 425 simulated IMs. For this purpose, the SLL values estimated by the proposed model are compared with empirical relations found in the IEEE 112 (Table I) [21], IEC 60034-2-1 (5) [22], and NEMA MG1 (Table II) [24] standards, (6) [20], and values calculated using method B in the IEEE 112 standard under various operating conditions.

Fig. 4 illustrates the SLL values calculated via the IEEE 112 standard, in comparison with the estimated values from the proposed model and the mentioned empirical relations, under conditions of rated load, 50 Hz, and without harmonics. Under the conditions mentioned, the proposed model's estimated SLL values show remarkable agreement with the calculated SLL, affirming its high accuracy. Conversely, empirical relations (5) and (6) and Tables I and II demonstrate weaker agreement with calculated SLL values when compared, indicating their insufficient accuracy for estimating SLL in the studied IMs. The results shown in Fig. 4 substantiate the proposed model's superior accuracy in SLL estimation.

Subsequently, the SLL estimation error for both the proposed model and existing relations, relative to the calculated values, is calculated for further analysis under full load, 50 Hz, and no harmonic conditions. Four error ranges are considered: 0-10%, 10%-20%, 20%-30%, and over 30%. The number of simulated IMs within each SLL estimation error range is then determined for both the proposed model and the existing empirical relations. Fig. 5 shows the number of studied IMs (as a percentage) falling into each SLL estimation error range under these specific operating conditions.

Referring to Fig. 5, it is observed that when using the proposed model, 52% of the simulated IMs have an estimation error below 10% compared to the calculated values. In contrast, when employing (6) and the NEMA MG1 standard, 81.4% and 78.1% of the studied IMs, respectively, exhibit an estimation error exceeding 30%. Furthermore, for the IEEE 112 standard, 45.2% of the IMs have an SLL estimation error greater than 30%, with only 22.3% of the IMs

having an estimation error less than 10%. For the IEC 60034-2-1 standard (5), 31.8% of the studied IMs have an SLL estimation error below 10%, and only 15.5% of the IMs have an estimation error greater than 30%. Although the estimation error of the relation provided by the IEC 60034-2-1 standard

is lower than that of other empirical relations, its accuracy in SLL estimation is still inferior to that of the proposed model. Therefore, the results presented in Fig. 5 indicate the high accuracy of the proposed model relative to the existing empirical relations in SLL estimation.

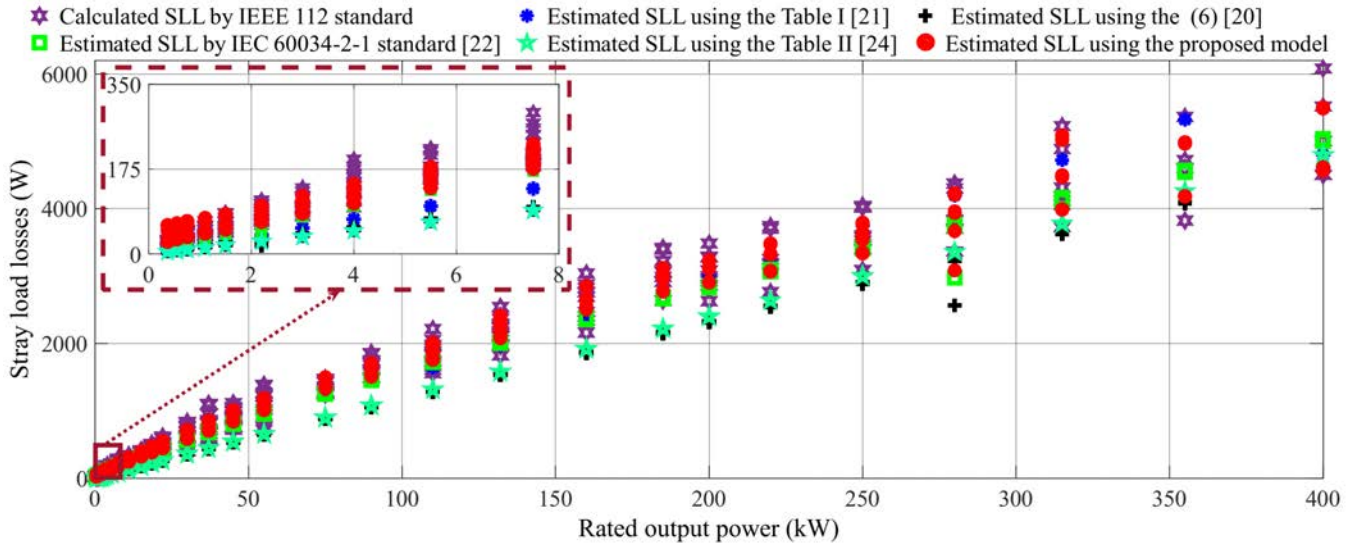


Fig. 4. Calculated and estimated SLL values for simulated IMs under full load, 50 Hz, and no harmonic conditions.

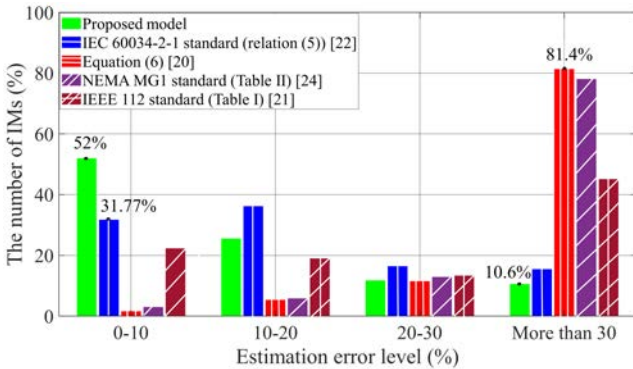


Fig. 5. The number of simulated IMs (in percentage) in each SLL estimation error level under full load, 50 Hz, and no harmonic conditions.

To comprehensively evaluate the performance of the proposed SLL estimation model under various operating conditions, in addition to full load, load points ranging from 40% to 120% of full load are considered. Furthermore, given that industrial IMs sometimes operate with harmonic-containing power supplies, which affect the SLL value, conditions with harmonic content at THD levels from 0% to 20% (in 5% increments) are considered for different load points. Subsequently, for each load point and THD level, the estimation error of the proposed model and existing empirical relations is calculated and categorized. Then, the average percentage error for each IM is computed across all load points and THD levels. Finally, the number of studied IMs in each SLL estimation error level is calculated for both the proposed model and the existing empirical relations.

Fig. 6 illustrates the number of studied IMs (in percentage) within each SLL estimation error level, in different load points and THD levels. The results from this figure indicate that under various operating conditions and when using the

proposed model, 50.3% of the simulated IMs have an average estimation error of less than 10%, while only 14.5% of the IMs exhibit an estimation error exceeding 30%. In contrast, the empirical relations provided in the IEEE112 and NEMA MG1 standards, as well as (6), demonstrate low accuracy in SLL estimation. Specifically, at least 71% of the studied IMs have an average estimation error greater than 30%, which is unacceptable.

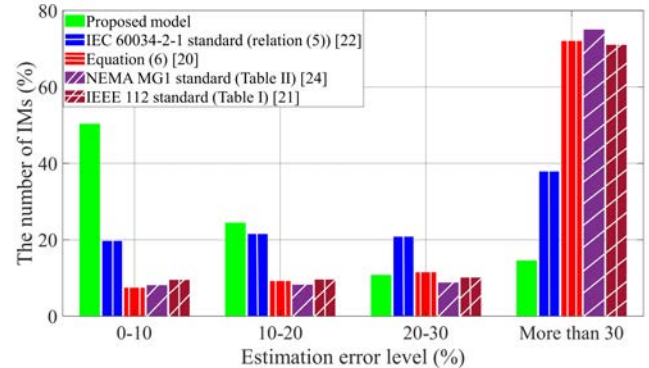


Fig. 6. The number of simulated IMs (in percentage) in each SLL estimation error level in different load points and THD levels.

For the IEC 60034-2-1 standard, 37.9% of the studied IMs have an average estimation error greater than 30%, and only 19.7% have an average estimation error of less than 10%, indicating a relatively low accuracy for this standard's relations in SLL estimation. Analysis of the results at each load point and THD level reveals that for the existing empirical relations, the average estimation error increases compared to the conditions of full load and zero THD. The reason for this increase in error for scenarios outside of full load and at various THD levels in estimating SLL losses is that these relations were developed solely based on operating

conditions at full load and without harmonic effects, and the impact of operating at load points other than full load has not been accounted for. Finally, the analysis of the results in Fig. 6 confirms that, unlike the existing empirical relations, the proposed model is capable of accurately estimating SLL under diverse operating conditions.

B. Quantitative Sensitivity Analysis

Two sensitivity analyses are conducted here: the first examines the effect of reference data uncertainty, and the second verifies the proposed model's causal response to THD and load variations.

1) Sensitivity to reference data uncertainty (IEEE 112-B)

The sensitivity analysis of the proposed MLP model was conducted to evaluate its performance against uncertainties in reference data of method B in IEEE 112. By simulating varying levels of uncertainty from 0% to 20%, the impact of changes in input parameters on key performance metrics, namely root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) were quantified. At 0% uncertainty, the results showed an RMSE of 164.57 W, a MAE of 88.32 W, and a MAPE of 12.53%. As the uncertainty increased to 20%, the RMSE escalated to 302.78 W, the MAE to 174.57 W, and the MAPE to 29.18%, indicating growth factors of approximately 1.83, 1.98, and 2.33, respectively. These quantitative results demonstrate that the model maintains a predictable performance, showcasing its robustness against reasonable levels of reference data uncertainty. The relationship between uncertainty and error metrics is illustrated in Fig. 7.

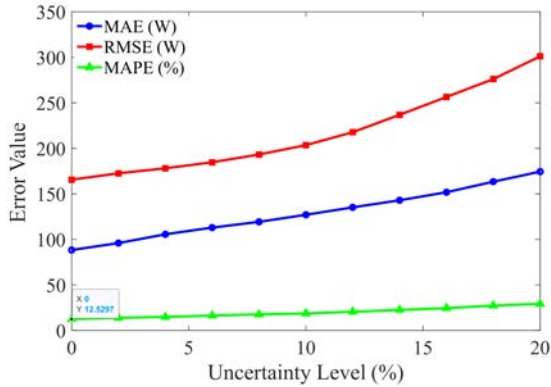


Fig. 7. Sensitivity analysis: uncertainty vs. error metrics (RMSE, MAE, and MAPE).

2) Sensitivity to input variables (THD and load)

This subsection quantitatively examines the internal causal relationships of the proposed MLP model by computing the partial derivative $\partial \text{SLL} / \partial \text{THD}$ and comparing it with the physically derived sensitivity (method B of IEEE 112 standard) across all load and THD levels. The analysis focuses on the non-linear coupling between THD and load to assess the model's physical consistency.

Fig. 8 presents the SLL estimated by the proposed MLP model versus those calculated according to method B of IEEE 112, as a function of THD at various load points for four

randomly selected IMs from the 425 IM dataset. The selected IMs cover a wide power range and different pole numbers. In all four cases, the MLP predictions closely follow the physically calculated SLL across the entire THD range from 0% to 20%. The excellent agreement, with MAPE values well below 11% and as low as 1.55%, demonstrates that the model successfully captures the nonlinear relationship between harmonic distortion and stray load losses. Notably, the error does not exhibit a systematic bias with motor size or pole count, indicating that the model generalizes well across different motor designs.

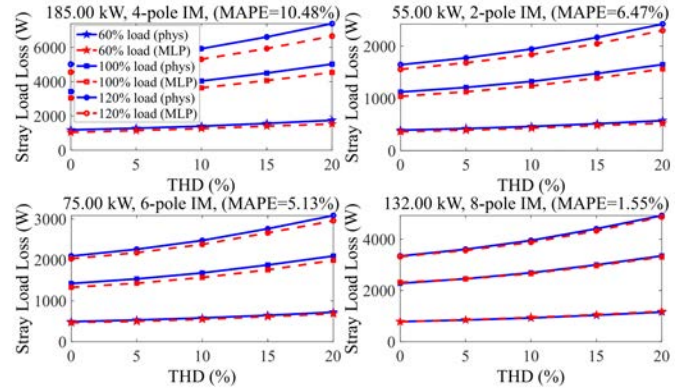


Fig. 8. Comparison of estimated and calculated SLL versus THD for four selected IMs at various loads.

Fig. 9 provides a more rigorous quantitative verification by comparing the partial derivative $\partial \text{SLL} / \partial \text{THD}$ obtained from the physical reference (method B of IEEE 112 standard) and from the MLP model for the best-performing IM in Fig. 8 (132 kW, 8-pole). The contour maps of sensitivity are plotted against load and THD. As can be seen, the two contour plots are visually almost identical: Both show that the sensitivity increases with load and is moderately higher for mid-range THD levels. This near-perfect match confirms that the MLP model has not only learned the final SLL values but also the underlying causal mechanism—i.e., how changes in THD affect SLL under varying load conditions.

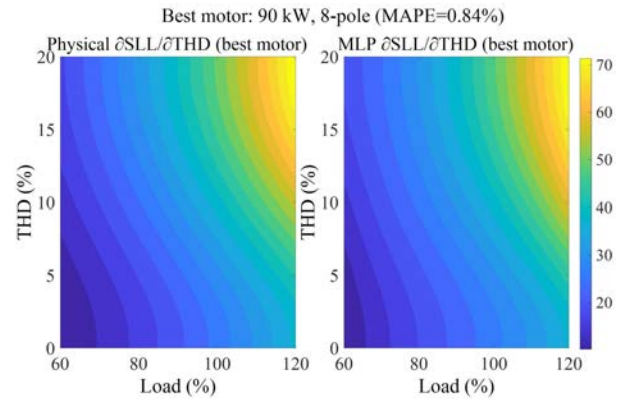


Fig. 9. Contour maps of physical and MLP-derived sensitivity $\partial \text{SLL} / \partial \text{THD}$ for the best-performing IM.

Fig. 10 shows the histogram of the correlation coefficients between the physical and MLP-derived sensitivities ($\partial \text{SLL} / \partial \text{THD}$) computed for all 425 IMs. The mean correlation coefficient is 0.902, with the majority of IMs

exhibiting correlations above 0.85. A correlation of this magnitude is widely considered “high” in engineering and ML contexts. The narrow spread of the histogram indicates that the model performs consistently well across the entire population of IMs, regardless of rated power or pole number. This statistical evidence substantiates the claim that the proposed MLP model has learned the physical relationship between THD and SLL in a causally consistent manner, rather than merely fitting the output values.

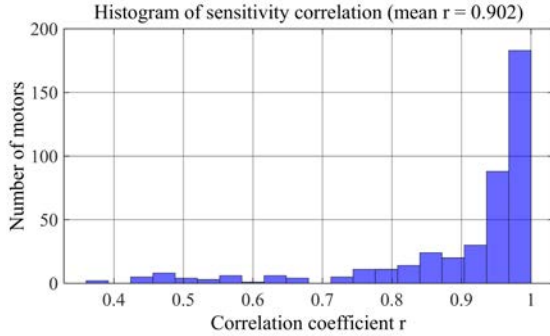


Fig. 10. Histogram of correlation coefficients between physical and MLP sensitivity across all 425 IMs.

In summary, the proposed MLP model accurately estimates SLL under distorted supply conditions and correctly captures the nonlinear coupling between THD and load. The high mean correlation (0.902), low sensitivity error (2.77 W%), and excellent agreement in contour maps confirm its physical consistency. Thus, the model offers a reliable, non-invasive alternative for SLL estimation.

V. EXPERIMENTAL SETUP AND VALIDATION

The effectiveness of the proposed SLL estimation model is experimentally validated in this study. This validation is performed by comparing estimations from the proposed model and empirical relationships against measured SLL values, following method B of the IEEE 112 standard. The experimental setup, illustrated in Fig. 11, consists of a digital power meter (measuring voltage, current, and input power), a magnetic powder brake and its controller for adjustable load torque, and an IM. Test IM specifications are detailed in Table VI. Due to the absence of a variable frequency drive (VFD) in the setup, SLL values were measured and estimated at 50 Hz, with no harmonics, across a range of load points. The study commenced with measuring full-load SLL values for the test IMs according to method B of IEEE 112 standard. This was followed by estimations using empirical methods and the proposed model.

TABLE VI
INFORMATION ON THE TESTED IMs

IM information	Motor 1	Motor 2	Motor 3	Motor 4
Fed voltage/V	220	380	380	380
Connection	Delta	Delta	Delta	Delta
Rated output power/kW	0.3	1.1	3	4
Number of poles	4	2	4	6
Current in full-load/A	1.4	2.5	6.5	9.6
Frequency/Hz	50	50	50	50
Speed in rated-load/(r/min)	1420	2825	1435	950

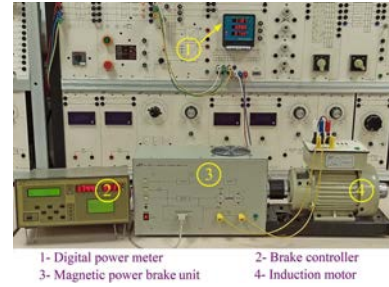


Fig. 11. The experimental setup for validation.

To measure the SLL of the test IMs according to method B of IEEE 112 standard, first, total losses are calculated by subtracting the output mechanical power from the input electrical power. Mechanical and iron losses are computed through a no-load test. Next, the stator and rotor copper losses are determined. The SLL value is then obtained by subtracting these iron, mechanical, and copper losses from the total measured losses, as shown in (1). The following step involves estimating the SLL values at rated load for the experimental IMs under various operating conditions using both the proposed model and established empirical relations. Table VII provides a comparative summary of the measured and estimated SLL values at full load (50 Hz) for the experimental IMs. The results presented in Table VII demonstrate that the proposed model yields estimations with only minor deviations from the measured SLL values for the studied IMs. However, the empirical relations, when compared to the measured data, reveal significant discrepancies in some cases, thus indicating a lower level of accuracy compared to the proposed model for SLL estimation.

According to Table VII, the proposed model exhibits a maximum estimation error of 6.16% at rated load and 50 Hz, occurring in the 0.3 kW IM. Conversely, the investigated empirical relations show a minimum error of 5.21% in the 3-kW IM, specifically with the IEC 60034-2-1 standard's relation. Other empirical relations yield higher errors, with the NEMA MG1 standard's relation for the 0.3 kW IM resulting in an error as high as 84.1%. These findings consequently underscore the questionable accuracy of empirical relations and affirm the superior precision of the proposed model.

TABLE VII
MEASURED AND ESTIMATED SLL VALUES OF THE TESTED IMs AT FULL LOAD AND 50 Hz FREQUENCY

	Procedure	0.3 kW	1.1 kW	3 kW	4 kW
		IM	IM	IM	IM
SLL value (W)	Measured [21]	22.7	46.1	84.3	115.7
	Estimated using the proposed model	24.1	47.8	84.2	118.2
	Estimated using the IEEE 112 standard (Table I) [21]	5.4	19.8	54	72
	Estimated using the IEC 60034-2-1 standard (5) [22]	9.9	33.9	79.9	107.4
	Estimated using the NEMA MG1 standard (Table II) [24]	3.6	13.2	36	48
	Estimated using (6) [20]	4.4	15.1	38.9	53.7
Estimation error (%)	Proposed model	6.16	3.69	0.12	2.16
	IEEE 112 standard	76.2	57.0	35.9	37.8
	IEC 60034-2-1 standard	56.4	26.5	5.21	7.17
	NEMA MG1 standard	84.1	71.4	57.3	58.5
	Relation (6)	80.6	67.2	53.8	53.6

Further evaluation of the proposed SLL estimation model for experimental IMs at different load points involved measuring SLL values at 60%, 80%, 100%, and 120% of rated load, with a 50 Hz supply and no harmonics. These measured SLL values were then compared against estimations derived from the proposed model and existing empirical relations. The estimation errors for SLL were subsequently calculated for both the proposed model and the empirical relations from the reviewed standards and (6) across these load points. The average SLL estimation error for each method at these various loads was then computed. Fig. 12 presents a comparison of the average SLL estimation error between the proposed model and existing empirical relations for the experimental IMs at these different load points.

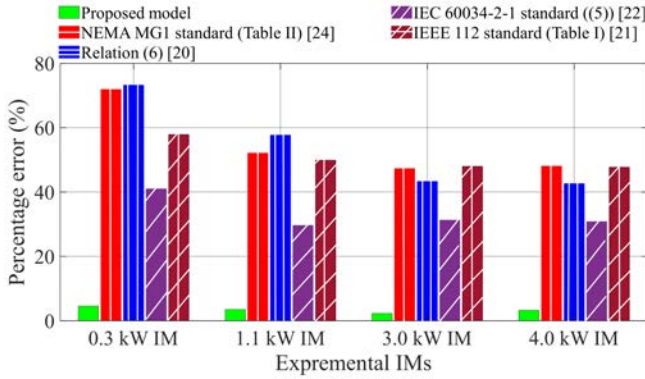


Fig. 12. The average SLL estimation error of the proposed model and existing empirical relations for the experimental IMs at the different load points.

As shown in Fig. 12, when using the proposed model, the average SLL estimation error for the experimental IMs across various load points is low, with a maximum average error of 4.56%. In contrast, using the empirical relations results in a high average SLL estimation error for the experimental IMs. Specifically, when utilizing the empirical relations provided by IEEE 112, IEC 60034-2-1, NEMA MG1, and (6), the minimum average SLL estimation errors for the IMs under study are 47.75%, 29.66%, 47.32%, and 42.63%, respectively. These values are high and considered unacceptable. Finally, Table VIII summarizes the average SLL estimation error at different load points for all experimental IMs. The findings presented in Fig. 12 and Table VIII underscore the accuracy of the proposed model in estimating SLL across various load points for these test IMs.

TABLE VIII
AVERAGE PERCENTAGE ESTIMATION ERROR OF SLL AT DIFFERENT LOAD POINTS FOR TESTED IMs

Method	Average percentage estimation error/%
Proposed model	3.4
IEC 60034-2-1 standard [22]	33.2
IEEE 112 standard [21]	50.89
(6) [20]	54.22
NEMA MG1 standard [24]	54.86

Although experimental validation is restricted to 50 Hz without harmonics, the proposed model's capability under harmonic distortion was validated via simulations in Section IV, encompassing a THD range of 0-20% across various load

points. These complementary approaches collectively validate the model's robustness.

VI. LIMITATIONS AND APPLICABILITY OF PROPOSED MODEL

Given the absence of ML-based techniques for estimating SLL in IMs and the superiority of MLP over other ML algorithms due to its strong function approximation and higher flexibility, this paper introduces a non-invasive model based on the MLP to address SLL estimation challenges. Its main strength lies in employing the MLP for non-invasive SLL estimation by relying solely on accessible and easily measurable inputs: nameplate data, input power, and THD. This accessibility makes the model particularly suitable for real-time monitoring and integration into embedded industrial systems, while offering a computationally less complex alternative to traditional numerical methods such as FEA. The development of this model, based on data from 425 simulated IMs and experimentally validated on four IMs (0.3, 1.1, 3, and 4 kW), provides a solid basis for its predictive capability.

However, the practical implementation of this model in industrial environments warrants careful consideration of potential challenges. Environments characterized by significant electrical noise could compromise the accuracy of the essential input measurements. Furthermore, the model's reliance on nameplate data assumes its accuracy and completeness, which may not always be the case for undocumented IMs in industrial settings. From a scope view, the model's generalizability beyond the tested power range (0.37-400 kW) and its applicability to non-standard motor designs or extreme operating conditions (e.g., highly nonlinear loads) would require further data collection and validation. Furthermore, it should be noted that the proposed model is developed based on a supply frequency of 50 Hz and has shown its applicability for estimating SLL in this specific frequency range. To accurately estimate SLL under different supply frequencies, the model needs to be retrained. Despite its data-driven nature, the proposed MLP model implicitly captures physical loss principles (e.g., THD-SLL correlation) due to its extensive training. Future work will leverage explainable AI to enhance interpretability.

VII. CONCLUSION

This paper introduces, for the first time, a new MLP-based model for non-invasive estimation of SLL in IMs. The model was developed through an in-depth analysis of SLL data obtained from simulations of 425 IMs in MATLAB software. By leveraging this extensive dataset and applying the MLP algorithm, a highly accurate model for SLL estimation in IMs has been established. The proposed model is non-invasive, as it relies solely on readily available inputs: nameplate information, input power, and the THD of the IM. Additionally, the suggested model, compared to existing empirical relations, is computationally efficient and appropriate for real-time applications.

To comprehensively evaluate the accuracy of the proposed SLL estimation model, its performance was assessed using

both simulated IMs and an experimental setup. For simulated IMs under diverse operating conditions, conventional empirical relations, including those from IEEE 112 and NEMA MG1 standards as well as (6), showed poor accuracy. Specifically, at least 71% of IMs had an average estimation error greater than 30%, rendering them unsuitable. Using the IEC 60034-2-1 standard, 37.9% of IMs exhibited errors exceeding 30%, and only 19.7% achieved errors below 10%. Experimental validation further confirmed these limitations, with empirical relations producing an average SLL estimation error of 33.24% across all scenarios for the test IMs. These findings clearly demonstrate that existing empirical relations cannot provide acceptable accuracy for SLL estimation. In contrast, the proposed MLP-based model demonstrated significantly improved performance. For simulated IMs, at least 50.3% achieved average errors under 10%, while only 14.5% exceeded 30%. For the experimental IMs, the model achieved a remarkably low average error of 3.4% across all test scenarios.

Sensitivity analysis revealed that the proposed model's performance metrics (RMSE, MAE, and MAPE) increased predictably as the uncertainty in the reference data grew, indicating a robust and well-behaved response to varying levels of input confidence. Moreover, a rigorous quantitative sensitivity analysis revealed that the model's partial derivative $\partial \text{SLL} / \partial \text{THD}$ correlated with the physically derived sensitivity at an average of 0.902, confirming that the proposed MLP correctly captures the nonlinear causal coupling between harmonic distortion and load. These results establish the superior accuracy and reliability of the MLP model for SLL estimation in IMs, highlighting its effectiveness across diverse operating conditions and validating its practical applicability. Finally, future work will include experimental validation using a VFD to further enhance and comprehensively assess the proposed model's performance under varied harmonic and frequency conditions, as well as extending the dataset to include IE4 motors.

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