Diagnosis of ITSC Faults in Stator Windings of Controlled PMSM: Entropy-Based Feature Extraction and MLP Classifier

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***Abstract*— This paper investigates the diagnosis of Inter-Turn Short-Circuit (ITSC) faults in Permanent Magnet Synchronous Machines (PMSM) under controlled experimental conditions. The study is based on stator current signals acquired for different speeds, load levels, and fault severities. Since time-domain waveforms under variable speed drive do not clearly reveal the fault, Shannon entropy is used to capture variations in signal complexity and extract a discriminative feature. This feature is then used as input to a Multi-Layer Perceptron (MLP) classifier. The experimental results show that the proposed approach can effectively distinguish healthy and faulty conditions, achieving mean values of 92.8% accuracy, 94% precision, 96.6% recall, and 95.2% F1-score. These results demonstrate the potential of Shannon entropy combined with MLP for reliable ITSC fault diagnosis in PMSMs.**

I. Introduction

Synchronous machines, particularly Permanent Magnet Synchronous Machines (PMSMs), play a crucial role in modern industrial applications due to their high efficiency, power density, and reliability [1]. They are widely used in electric vehicles, renewable energy systems, and industrial drives [2]. However, their continuous operation under varying load and environmental conditions makes them vulnerable to different types of faults, among which stator winding Inter-Turn Short-Circuit (ITSC) faults are considered one of the most critical. These faults can lead to severe performance degradation, excessive heating, and, if not detected at an early stage, catastrophic machine failure [3].

ITSC faults are particularly challenging to detect in their early stages under PWM control due to their subtle signatures and the nonlinear behavior they introduce into the system. As highlighted in recent studies, stator winding faults account for a significant proportion of electrical machine failures, and their early detection remains an active area of research [4]–[7]. Traditional fault diagnosis techniques rely mainly on signal processing approaches such as motor current signature analysis, in which frequency-domain features are extracted using the Fast Fourier Transform (FFT). Although FFT-based methods are effective at identifying characteristic fault-related harmonics, they often suffer from limitations when dealing with non-stationary signals, noise, and low-severity faults [8]–[10].

To overcome these limitations, advanced data-driven approaches based on Artificial Intelligence (AI) have been increasingly adopted [11]. Machine learning techniques, including artificial neural networks, support vector machines, and deep learning models, have demonstrated strong capabilities in fault detection and classification tasks by learning complex nonlinear relationships from data [12]–[14].

A key challenge in AI-based fault diagnosis lies on selecting informative features. While FFT provides frequency-domain information, alternative feature extraction methods based on information theory, such as Shannon entropy, have gained attention for their ability to quantify signal complexity and disorder. Entropy-based features are particularly suitable for detecting subtle changes in signal patterns and are known to be more robust under noisy and non-stationary conditions [15]–[19]. These characteristics make them promising candidates for improving fault diagnosis performance in electrical machines.

In this context, this paper investigates a feature extraction approach for ITSC fault diagnosis in synchronous machines based on Shannon entropy. The extracted entropy-based feature is then used to train a Multi-Layer Perceptron (MLP) classifier, whose performance is evaluated in terms of accuracy, robustness, and fault discrimination capability. The main contribution of this work is to demonstrate the effectiveness of Shannon entropy as a discriminative feature for enhancing AI-based diagnosis of ITSC faults in synchronous machines.

The remainder of this paper is organized as follows. Section II presents the experimental setup and the data acquisition process. Section III introduces the Shannon entropy-based analysis and highlights its discriminative capability for ITSC fault diagnosis. Section IV describes the MLP-based classification approach. Finally, Section V concludes the paper.

II. Experimental Setup and Data Acquisition

All the results presented in this work are obtained from an experimental test bench specifically designed for the analysis and diagnosis of ITSC faults in synchronous machine.

A. Experimental Test Bench

The test bench consists of a 4.4 kW PMSM mechanically coupled to a 7 kW Permanent Magnet Synchronous Generator (PMSG). The generator is connected to an 8 kW resistive load bank, which is used to emulate the mechanical load applied to the PMSM. The experimental test bench is shown in Fig. 1.

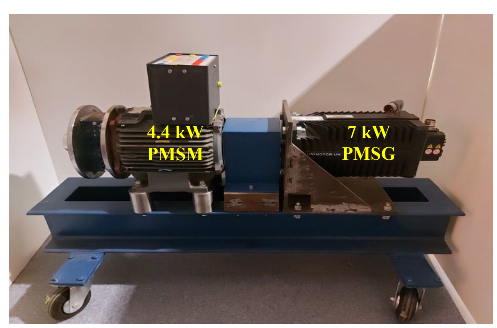

Figure 1. Machine test bench.

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To study ITSC faults under controlled conditions, the stator winding of the PMSM was rewound to allow the intentional introduction of ITSC faults at different severity levels. This modification enables the generation of reproducible fault scenarios while maintaining the overall structure of the machine.

The PMSM is driven by a vector control strategy based on Field-Oriented Control (FOC). The control system is implemented using a DC bus, which supplies a three-phase voltage inverter, and a real-time digital signal processing platform (dSPACE MicroLabBox). This setup allows accurate control of the machine currents, speed, and torque, as well as real-time data acquisition for diagnostic purposes.

All relevant parameters of the experimental test bench are summarized in the Appendix.

B. Data Acquisition and Dataset Description

In this paper, the fault diagnosis is based on the analysis of stator phase currents. Each phase is equipped with a high-precision current sensor (HIOKI CT6873), which is used both for the control of the machine and for data acquisition purposes. These sensors provide accurate current measurements that are essential for capturing fault-related signatures under various operating conditions.

The current signals are acquired using a four-channel digital oscilloscope (Tektronix MDO3034). A high sampling frequency of 250 kHz is employed in order to accurately capture the fast dynamics and switching harmonics introduced by the PWM inverter, which are critical for reliable fault diagnosis.

The acquired data are used to build both training and testing datasets for the proposed diagnostic approach. In total, 132 samples are collected, with each sample corresponding to a time duration of 0.4 s. The experiments are conducted at multiple operating speeds, namely 400, 600, 800, 1000, 1300, and 1500 rpm, to capture a wide range of dynamic conditions.

For each speed, several load levels are considered: 20%, 40%, 60%, 80% and 100% of the nominal load. Under each operating condition, the machine's health states are evaluated, including a healthy condition and three levels of ITSC faults, corresponding to 1/3 and 2/3 of the elementary coil and the entire elementary coil being affected by the fault. This allows the creation of a dataset that reflects varying fault severities.

In addition, experiments at low speed (200 rpm) are conducted for selected load levels of 40%, 60%, and 80% of the nominal load, to further assess the robustness of the proposed diagnostic approach under low-speed operating conditions. This comprehensive dataset ensures representative coverage of operating regimes, fault severities, and load variations for the evaluation of the classification models. A database diagram is presented in Fig. 2.

III. SHANNON ENTROPY-BASED ANALYSIS

Shannon entropy, originally introduced in information theory [20], is a widely used measure for quantifying the uncertainty or complexity of a signal. In the context of fault diagnosis, it provides valuable information about the distribution and variability of measured signals, making it particularly suitable for detecting subtle changes caused by incipient faults [21]–[23].

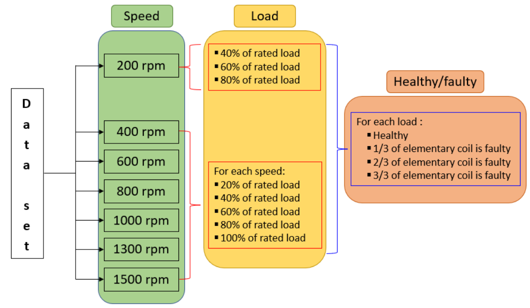


Figure 2. database diagram.

A. Theoretical Background of Shannon Entropy

For a given time series $\{x_1, x_2, \ldots, x_n\}$, the Shannon entropy $H(x)$ is defined as follows:

$$H(x) = -\sum_{i=1}^{n} p(x_i)\log_2\big(p(x_i)\big) \tag{1}$$

where p denotes the probability associated with the time series value (x_i). The term $\log_2\big(p(x_i)\big)$ represents the length of its binary encoding. Accordingly, it quantifies the information content of (x_i) with the unit expressed in bits [24]. The entropy $H(x)$ represents the average amount of information contained in the signal.

In practical applications, the probability distribution is estimated from the amplitude histogram of the measured signal using the Matlab "histocounts function" with an automatic bin selection. The influence of fixed bin count was not investigated in this study and will be considered in future works. The signal is discretized into a finite number of intervals, and the probability of each bin is computed as the normalized frequency of occurrence. This approach transforms the time-domain signal into a statistical representation suitable for entropy computation.

A signal characterized by a uniform amplitude distribution yields a high entropy value, reflecting a high level of randomness. In contrast, a signal with a more concentrated distribution exhibits lower entropy. Therefore, Shannon entropy serves as an effective indicator of changes in signal complexity induced by faults.

B. Limitations of Time-Domain Analysis under PWM Control

To illustrate the limitations of time-domain analysis, Figs. 3 and 4 show the stator phase currents under healthy and faulty conditions at two different operating speeds (1300 rpm and 400 rpm). It can be observed that, despite the presence of ITSC fault (Fig. 3(b) and Fig. 4(b)), the current waveforms remain very similar in both cases. The differences between the healthy and faulty states are not clearly distinguishable. This is mainly due to the influence of PWM control. As a result, visual inspection of the current waveforms does not provide reliable information for fault detection, highlighting the need for more advanced signal processing techniques.

In electrical machines operating under PWM control, switching harmonics and nonlinear effects significantly modify the statistical distribution of current signals. As a result, entropy-based feature is particularly effective for capturing these variations, even when they are not clearly observable in the time domain.

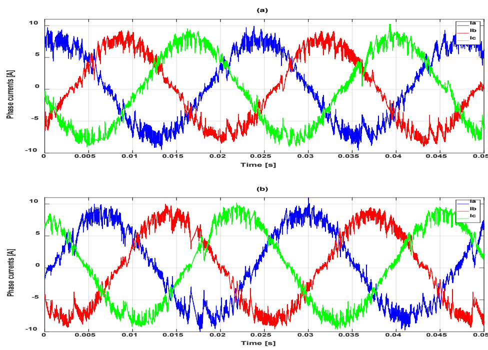


Figure 3. Stator currents at 1300 rpm with 60% load : (a) at healthy state and (b) with 2/3 of the turns in serie-connected coil of phase b are short-circuited.

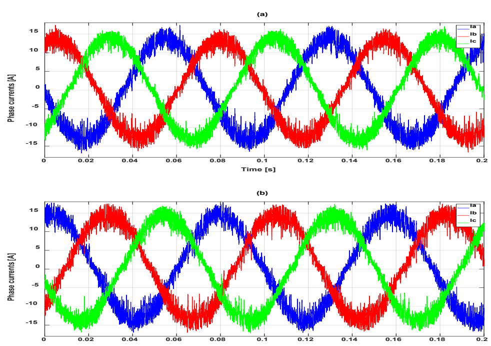


Figure 4. Stator currents at 400 rpm with 100% load : (a) at healthy state and (b) with 3/3 of the turns in serie-connected coil of phase b are short-circuited.

C. *Entropy-Based Feature Extraction and Analysis*

To overcome the limitations of time-domain analysis, Shannon entropy is used as a feature for fault diagnosis. The entropy is computed from the amplitude distribution of the stator current signals.

For each operating condition, including different speeds and load levels, the entropy values are calculated and analyzed. Fig. 5 shows the distribution of entropy values for various operating conditions at 1500 rpm and 800 rpm, including healthy and faulty states.

A detailed analysis of Fig. 5 and 3D entropy surfaces plotted in Fig. 6, provides several important insights into the behavior of the proposed feature. First, it is observed that the entropy values corresponding to faulty conditions are generally higher than those of the healthy state across most operating conditions. However, in some cases, at 100% load, this trend becomes less pronounced, which can be attributed to magnetic saturation effects that alter the signal distribution.

Regarding the separability of the different states, no overlap is observed between the entropy values of healthy and faulty conditions, indicating a clear distinction between classes. This highlights the strong discriminative capability of Shannon entropy for ITSC fault diagnosis.

The influence of the load level on entropy values is non-monotonic. While entropy increases from 20% to 40% load, it decreases at 60% load and then increases again at higher loads (80% and 100%). This behavior reflects the complex interaction between load conditions and the statistical properties of the current signals.

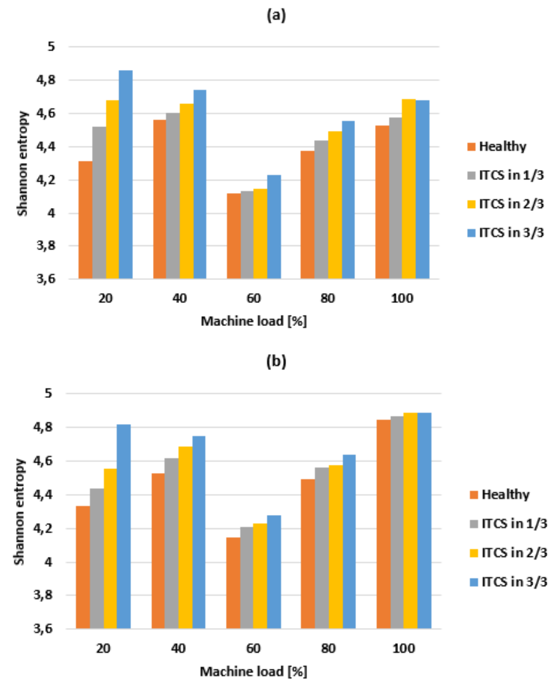
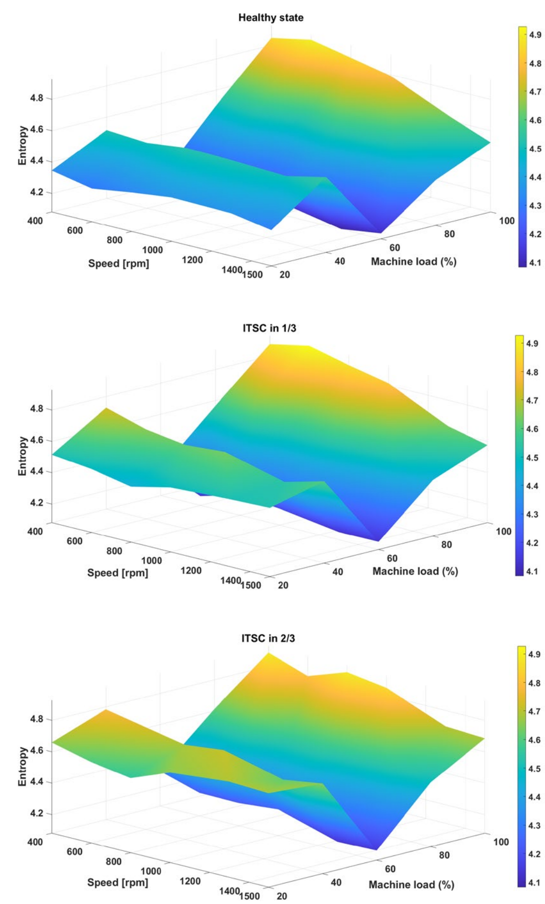


Figure 5. Entropy under different loads with healthy and faulty states: (a) at 1500 rpm and (b) at 800 rpm.



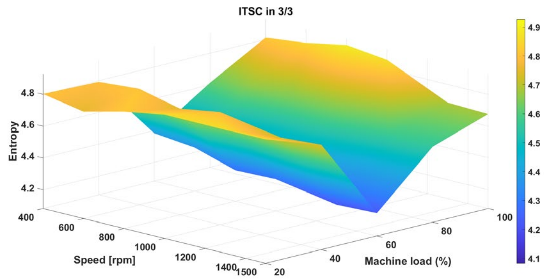


Figure 6. 3D representation of Shannon entropy as a function of speed and load for different machine conditions.

Interestingly and as is seen in Fig. 7(a), the fault becomes more distinguishable at lower load levels (20% and 40%), where the difference between healthy and faulty states is more significant. This is confirmed by the observed entropy deviations between each fault level and the healthy condition, which are larger at low loads than at high loads.

In Fig. 7(b), delta entropy remains positive across the entire speed range for all fault levels, confirming that faulty states consistently exhibit higher entropy values than the healthy condition. Regarding the influence of speed, the entropy difference remains relatively stable across the entire speed range, with only minor variations observed. This indicates that the operating speed has a limited impact on the entropy-based feature.

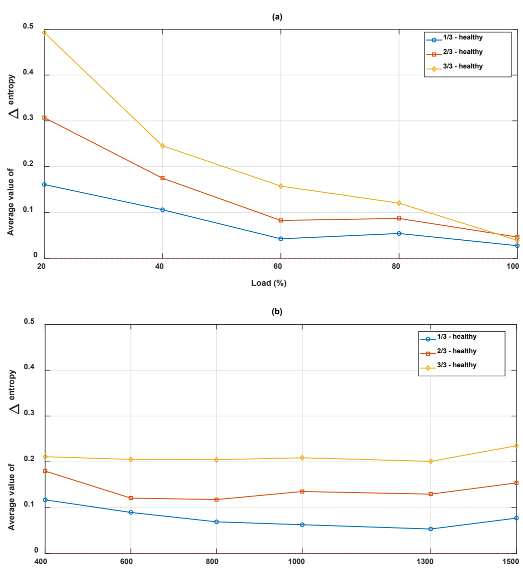


Figure 7. Average evolution of Δ entropy: (a) as a function of load and (b) as function of speed.

Finally, the effect of fault severity is clearly reflected in the entropy values. Across all load conditions, entropy follows a consistent increasing trend with fault severity: the 3/3 faulty condition exhibits the highest entropy, followed by the 2/3 and 1/3 fault levels, while the healthy condition consistently shows the lowest entropy. This behavior confirms that Shannon entropy is sensitive not only to the presence of a fault but also to its severity.

These results demonstrate that Shannon entropy provides a highly discriminative feature for ITSC fault diagnosis, enabling reliable separation between fault conditions across a wide range of operating scenarios. These properties make it particularly well-suited for integration into machine learning-based diagnostic frameworks.

IV. MLP Approach

MLP is a type of neural network used in machine learning to solve problems like classification or prediction.

It is organized in layers: an input layer that receives the data, one or more hidden layers that process it, and an output layer that produces the result. Each unit (or neuron) in a layer is connected to the next one, and these connections have weights that adjust as the model learns.

An MLP with one hidden layer using a sigmoid activation function was employed. The hidden layer contains n neurons, while the linear output layer, composed of a single neuron.

When data passes through the network, each neuron applies a simple calculation followed by an activation function, enabling the model to capture more complex, nonlinear patterns.

The MLP learns by comparing its predictions to the correct answers and then gradually correcting its weights using a method called backpropagation. This process is repeated many times until the model becomes more accurate.

In practice, MLPs are widely used because they are relatively simple but still powerful enough to handle a variety of real-world tasks [25], [26].

In this work, the MLP is used to detect ITSC faults, as shown in the following figure, at different severity levels.

In the following part we use the MLP approach with Shannon entropy feature in the input.

A. Training an AI Model using Entropy Feature

In this step, the main objective was to evaluate whether Shannon entropy can be used to detect faults in a motor. The idea was to rely solely on raw signals measured from three sensors (CH1, CH2, and CH3), without extensive preprocessing.

From these signals, entropy values were extracted and used as input features to train an MLP classifier model. Finally, the dataset was divided into two parts: 80% was used for training the model, and the remaining 20% was kept for testing its performance.

For this approach, a Python script was developed. The following steps were carried out:

- Automatic loading of CSV files,
- Filtering of CH1, CH2, and CH3 signals using a Butterworth low-pass filter to remove high-frequency noise,
- Feature extraction,
- Data scaling (standardization),
- Splitting the dataset into training and testing sets (80% / 20%),
- Training an MLP model,

- Evaluation using standard metrics (accuracy, recall, F1-score, confusion matrix).

The extracted feature is based on Shannon entropy, computed for each sensor.

In this experiment, we used an MLP classifier by splitting the data according to different load levels (20%, 40%, 60%, 80% and 100%).

For each CSV file, we calculated the Shannon entropy of the three sensor signals. These values were then used as input features for the MLP model.

To keep things clear and consistent, the code was slightly modified to group the data by load level, train a separate model for each group, and then evaluate the performance of each model. The metrics of evaluation are given in the following section.

B. Metrics

Each machine learning task requires performance measures to assess the fit between the model and the data. They are used to monitor and measure the performance of a model during and after training [27].

1) Accuracy

Classification accuracy is one of the simplest metrics in machine learning and is defined as the percentage of the number of correct predictions divided by the total number of predictions.

2) Precision

There are many situations where classification accuracy is not a reliable indicator of the model's performance. One of these scenarios is when a class distribution is imbalanced (one class is more common than the others). In this case, even if the model predicts all samples to be the most frequent class, it can still achieve a high accuracy, which is misleading.

3) Recall

Recall shows how effectively the model identifies positive cases. In other words, it indicates the proportion of actual positive samples that are correctly identified by the model.

4) F1-score

The F1-score combines precision and recall into a single value. It is particularly useful when a balanced measure is needed, as it accounts for both missed detections and false alarms.

C. Results and Discussions

The obtained results indicate these metrics for different load levels in the following Table:

TABLE I. VALUES OF DIFFERENT METRICS WITH MLP CLASSIFIER APPLIED FOR ITSC DIAGNOSIS

Load	Accuracy	Precision	Recall	F1-score
20%	100%	100%	100%	100%
40%	100%	100%	100%	100%
60%	100%	100%	100%	100%
80%	89%	87%	100%	93%
100%	75%	83%	83%	83%
Mean	92.8%	94%	96.6%	95.2%

The results obtained show at low loads (20%, 40%, and 60%), that the model achieves perfect performance (100% for Accuracy, Precision, Recall, and F1-score). This means that under these conditions, the model fully separates healthy and faulty states without any errors. All faults are correctly detected, and no false alarms are produced.

When the load increases to 80%, a slight drop in performance is observed. Accuracy decreases to 89% and the precision to 87%, indicating the presence of some false alarms (false positives). However, recall remains at 100%, meaning that the model still detects all faults without missing any. In other words, the model becomes more conservative preferring to flag potential faults even if it occasionally produces false alarms.

At full load (100%), the performance decreases further. The accuracy drops to 75%, and both precision and recall fall to 83%. This shows that under high stress conditions, the model struggles more to distinguish between healthy and faulty states, leading to false negative.

This approach performs very well at low and medium load levels. However, its performance decreases under full-load conditions. This degradation is mainly attributed to the limited DC-bus voltage, which was insufficient to maintain the rated machine voltage at 100% load. Consequently, the machine draws higher currents, leading to increased magnetic saturation and reduced separability between healthy and faulty conditions.

Overall, the classifier achieves high average performance, with mean values of 92.8% for accuracy, 94% for precision, 96.6% for recall, and 95.2% for F1-score. These results confirm the effectiveness of the proposed entropy-based feature extraction combined with the MLP classifier for ITSC fault diagnosis. Furthermore, the consistently high recall across all load conditions highlights the reliability of the approach in detecting faults, which is a critical requirement for practical diagnostic systems.

In fact, this strategy produced the best results of our study, especially when using entropy-based feature, demonstrating its effectiveness and strong potential for future industrial applications.

To make this system usable in practice, a possible solution would be to combine these models into a hybrid architecture: a first model would automatically detect the motor load, and then a corresponding load-specific model would be used to determine whether an ITSC fault is present.

V. CONCLUSION

This paper presented an experimental study on the diagnosis of ITSC faults in PMSM based on Shannon entropy and an MLP classifier. The analysis showed that time-domain current signals under variable speed operation do not clearly reveal fault signatures, highlighting the need for more advanced feature extraction techniques.

Shannon entropy was used to characterize the statistical properties of the stator current signals. The results demonstrated that entropy values provide clear separation between healthy and faulty conditions and are sensitive to fault severity across different operating regimes. In particular, the entropy-based analysis remained effective under varying speeds and load levels, although reduced separability was observed at high load due to saturation effects.

The MLP classifier trained on entropy features achieved high performance, especially at low and medium load levels, with an overall accuracy of 92.8%, a recall of 96.6%, and a F1-score of 95.2%. The proposed approach shows strong potential for industrial PMSM monitoring and predictive maintenance, enabling reliable ITSC fault detection using only stator current measurements under varying operating conditions. Compared with conventional spectral methods, the proposed entropy-based approach provides a compact and efficient representation of signal complexity under PWM control.

APPENDIX

P_n [kW]	4.4	**Ω_n [rpm]**	1500	**$f_{sampling}$ [kHz]**	250
U_n [V]	400	**pole pairs**	2	**N_{slot}**	36
I_n [A]	10	**$f_{switching}$ [kHz]**	10	**$N_{turns/slot}$**	36

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