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Article

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Estimation of the eddy current losses in a dry-type 3000 KVA transformer with machine learning

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Abstract

This paper explores the design parameters of high-voltage coils of three-phase transformers and the effects of eddy current losses caused by energy conversion. The commercial software, ANSYS-Maxwell, was employed to conduct the simulation of electrical and magnetic fields. The design parameters of the high voltage coil include the leg distance of core, the height and the block thickness of primary windings, the height of primary coils, and the height of secondary windings. The specification of the three-phase transformer of this study are 3000 kVA with rated voltage of 6600 V and corresponding current of 151.5 A. Base on thirty cases of simulation, machine learning, artificial neural network, was utilized to predict the extra loss due to eddy current in the clamps and the windings. The prediction accuracies are 0.72 and 0.86 for primary and secondary windings, respectively.

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Keywords: Dry-type transformer; Eddy current loss; Numerical simulation; Machine learning

1. Main text

Transformer is an important device in power supply and distribution networks. The high-frequency transformers have drawn much attention in recent years with the need high power electrical power conversion [1,2]. The dry-type transformers are increasingly utilized because of safety and environmental friendly. However, the size of dry-type transformer is larger and consequently the price of dry-type transformer is higher than oil type one [3].

In the design work of transformer, careful attention has to be paid on the core and winding loss mechanisms. The estimation of eddy current losses for core and winding is essential to eliminate possible hot spots and reduce stray losses. The eddy losses of transformers have a considerable economic impact on the operation of electrical systems.

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Due to the complexity of winding geometries and interactions between conductors in windings, it is difficult to find a general analytical solution for the eddy current losses in windings [4].

There are several approach to estimate eddy current losses, such as empirical models, the loss separation methods, and the hysteresis models [5]. Numerical methods such as finite element analysis (FEA) are widely employed to calculate eddy-current models in order to find the field solutions. Though it is difficult to use FEM to simulate the Litz-wire due to the long computation time [6], computational simulation still is a convenient approach in building features of physical models.

Although there have been many studies on transformer and eddy current loss, due to too many parameters in design, there is no systematical analyses in literature to study input and output data. The loss values of each part cannot be measured with systematical adjustment of the parameters. Therefore, a large amount of data could be obtained through combination of numerical simulation with technology of machine learning, it is worthwhile to try to find the best design for energy saving and material saving. Neural networks have been used to find the best way to make magnetic materials based on finite elements [7]. The design of the transformer can also be optimally designed in this way in combination with numerical methods [8].

In the present investigation, a numerical 3-D model was established to estimate the eddy current loss of a dry-type 3000 kVA transformer. Thirty cases of simulations have been performed for machine learning to establish relationships between geometry parameters and eddy current loss. The main objective of present study is to find the relationship between geometry parameters and the eddy current for each components.

2. Numerical model

The copper losses of primary windings, secondary windings, and clamps in a transformer were studied with numerical model. The model of the transformer is schematically shown in Fig. 1, which contains primary windings, secondary windings, a core, and four clamps. The small subsidiary parts were neglected for convenience of model construction. One primary winding was composed of eight coil blocks. The gap between two adjacent blocks was determined by coil height and the primary winding height. One secondary winding includes four parts of coils with three ducts between adjacent parts. A real winding is composed of many turns of wire curling around core leg. For feasibility of modeling and meshing, the turns were built as concentrated hollow regular polygons. Only half of the whole transformer was modeled since the electromagnetic field was symmetric.

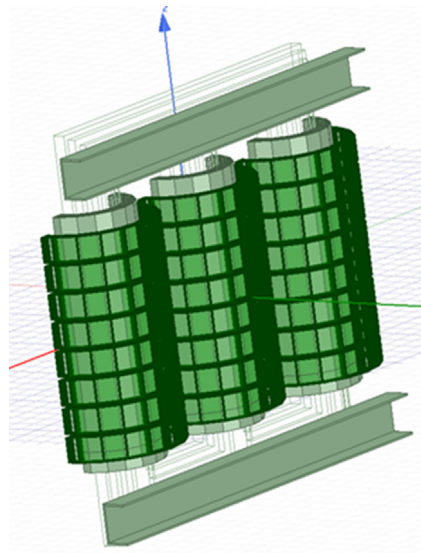


Fig. 1. Physical model for the present study.

In the study, geometrical parameters were adjusted to estimate the copper loss while the primary voltage and the primary current were kept the same. Besides, the cross section areas of primary windings and secondary windings

were also kept constant, respectively. The extra losses due to eddy current were estimated for various designs. The parameters include spacing of core leg (P1), primary winding height (P2), secondary winding height (P3), primary coil height (P4), and primary winding thickness (P5).

The materials of coils were considered as copper. Since the coils were insulated with very thin PET membranes, the conductivity of the coils was considered as mixture of conductor and PET insulator. The modified material properties were set according to the cross-section area percentage of the conductors in the primary and the secondary coils. Due to temperature rise in the windings, the conductivity was further modified as that at 120 °C. The material of the clamps was set as cast iron with corresponding relative permeability. The surface effect of eddy current on clamp was considered. The material of the core was set as silicon steel.

The electromagnetic field analysis was conducted with finite element method and a commercial code, Maxwell, was utilized. The applied mean voltage in primary winding was 6600 V and the total resistance was set to obtain the anticipated mean current, 151.5 A. The total power of three phases is 3000 kVA. The whole magnetic field range is about twice the total size of the transformer, and the magnetic flux on the far boundaries was set to be zero. For a specified geometry design, electromagnetic fields with and without eddy current were simulated to estimate the copper losses, respectively. The mesh of the field was refined during iteration based on the gradient of electromagnetic field. The convergence criterion was set as energy variation less than 0.003. According to the simulation results, the total number of grids is between 800,000 and 1.5 million.

3. Results and discussions

Fig. 2 shows the power loss of windings containing eddy current in a typical case. It is noted that eddy current mainly occurs at the top and bottom regions of coils. This is due to the magnetic flux crossing over the two edges.

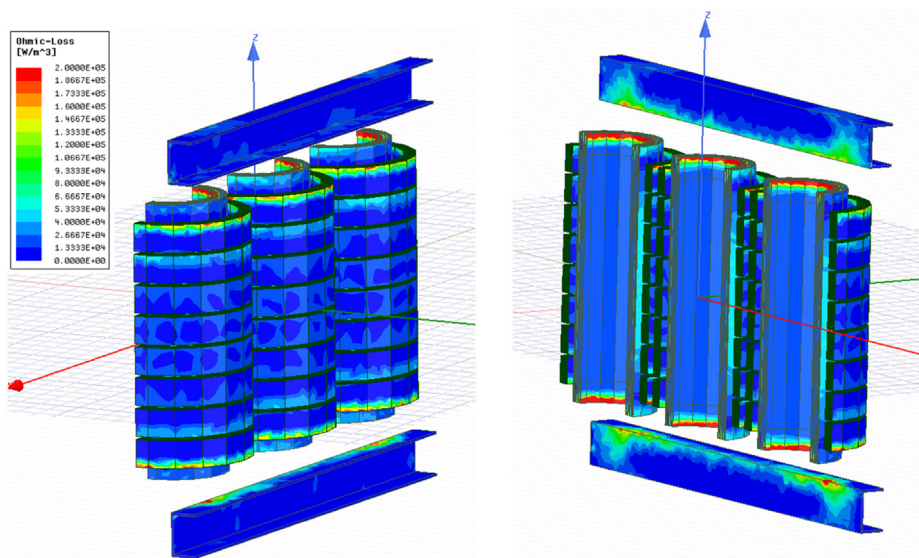


Fig. 2. The loss in the windings containing eddy current.

Thirty cases with various geometrical designs were simulated. The parameters P1~P5, the copper loss in clamps (A), the loss increment in primary windings (B), and the loss increment in the secondary windings (C) are listed in Table 1.

Artificial neural network was employed to conduct machine learning on the copper losses with eddy current. The parameters P1~P5 were taken as input neurons. The copper loss in clamps, the loss increment in primary windings, and the loss increment in the secondary windings were taken as output. There were three hidden layers in the machine learning. The maximum number of parameters was eight during the training process. The learning results were shown in Table 2. It is found that the square root of error converges when the learning rate ranges from 0.005 to 0.0001. It is also noted that the estimation in the clamps is very accurate, corresponding to about 6 W.

Table 1. The data for various input parameters and output.

P1 (mm)	P2 (mm)	P3 (mm)	P4 (mm)	P5 (mm)	A (W)	B	C
750	1105	1250	125	57.024	186.0	0.267	0.171
750	1170	1235	120	59.400	186.0	0.212	0.151
750	1190	1250	135	52.800	185.0	0.178	0.143
750	1220	1250	135	52.800	186.0	0.155	0.156
750	1250	1250	135	52.800	198.0	0.120	0.163
750	1140	1255	125	57.024	188.0	0.227	0.147
750	1215	1250	130	54.780	196.0	0.172	0.145
750	1246	1257	140	50.900	194.0	0.129	0.168
800	1166	1255	130	54.780	184.0	0.203	0.142
800	1180	1250	130	54.780	182.0	0.190	0.144
800	1194	1250	130	54.780	192.0	0.183	0.138
800	1220	1260	135	52.800	194.0	0.159	0.147
800	1246	1252	140	50.900	188.0	0.125	0.174
850	1126	1255	125	56.760	176.0	0.235	0.155
850	1206	1250	135	52.800	174.0	0.170	0.149
850	1220	1259	135	52.800	186.0	0.158	0.149
850	1241	1240	142	50.160	166.0	0.123	0.171
850	1244	1235	138	51.645	168.0	0.129	0.183
770	1159	1250	130	54.780	181.0	0.207	0.144
770	1132	1242	124	57.486	180.0	0.229	0.150
780	1108	1238	121	58.910	182.0	0.259	0.163
780	1225	1252	140	50.900	184.0	0.142	0.156
790	1168	1255	125	56.760	193.0	0.228	0.128
790	1081	1220	115	61.980	172.0	0.283	0.173
795	1240	1250	120	59.400	208.0	0.188	0.183
820	1255	1260	135	52.800	196.0	0.136	0.175
825	1140	1255	125	56.760	182.8	0.239	0.134
825	1164	1265	128	55.688	199.2	0.219	0.143
835	1100	1245	255	55.910	176.0	0.266	0.170
835	1248	1240	250	57.020	170.0	0.120	0.178

Table 2. The machine learning results with various learning rate.

Learning rate	0.005	0.0005	0.0001	FEM average	Accuracy
Loss of clamp (training/test) (W)	3.64/6.65	2.76/6.34	3.46/6.32	185.1 W	0.97
Loss increment in primary windings (%)	5.66/6.0	5.0/5.39	4.90/5.39	0.188	0.72
Loss increment in secondary windings (%)	3.74/4.0	1.76/2.53	1.38/2.14	0.156	0.86

The prediction of the extra loss due to eddy current in the windings is less accurate. According to the losses in the primary and secondary windings, about 4550 W and 4350 W, the error is about 220 W. This is small compared with the total loss. More considered factors or more learning cases may increase the accuracy.

4. Conclusions

Numerical analysis and machine learning of a dry-type 3000 kVA transformer has been conducted for various geometrical parameters. Brief summaries are listed as following:

1. The eddy current loss of clamps ranges from 170 W to 208 W. The error is 3.46 W for training data and 6.32 W for test data, showing over fitting of the data set.
2. The loss increment in the secondary has higher accuracy than that in the primary windings during machine learning.
3. Learning rate of 0.0001 shows good learning results compared with that of 0.005.
4. More cases should be done in order to obtain a more accurate prediction on the eddy loss of transformer.

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References

- [1] Islam MR, Guo Y, Zhu J. A high-frequency link multilevel cascaded medium-voltage converter for direct grid integration of renewable energy systems. *IEEE Trans Power Electron* 2014;29:4167–82.
- [2] Wei S, Fei W, Boroyevich D, Tipton CW. High-density nanocrystalline core transformer for high-power high-frequency resonant converter. *IEEE Trans Ind Appl* 2008;44:213–22.
- [3] Wu W, Kern JA. Temperature rise prediction of a natural cooling dry-type transformer. In: *IEEE southeast con 2016*, March 30–April 3. Norfolk, VA, USA; 2016.
- [4] Nan X, Sullivan CR. Simplified high-accuracy calculation of eddy-current loss in round-wire windings. In: *35th annual IEEE power electronics specialists conference*. Aachen, Germany; 2004.
- [5] Agheb E, Høidalen HK. Modification of empirical core loss calculation methods including flux distribution. *IET Electr Power Appl* 2013;7:381–90.
- [6] Liu X, Wang Y, Zhu J, Guo Y, Lei G, Liu C. Calculation of core loss and copper loss in amorphous/nanocrystalline core-based high-frequency transformer. *AIP Adv* 2016;6. 055927.
- [7] Tsekouras G, Kiartzis S, Kladas AG, Tegopoulos JA. Neural network approach compared to sensitivity analysis based on finite element technique for optimization of permanent magnet generators. *IEEE Trans Magn* 2001;37(5):3618–21.
- [8] Georgilakis PS. *Spotlight on modern transformer design*. Springer; 2009.