



Ain Shams University  
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# **Fault Classification in Transmission Lines Using Artificial Intelligence Techniques**

**M.Sc. Thesis**

**By**

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قسم هندسة القوى والآلات الكهربائية

عنوان الرسالة

## تصنيف الأخطاء في خطوط النقل باستخدام طرق الذكاء الاصطناعي

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## **Abstract**

Power transmission lines are the vital links in power systems providing the essential continuity of service from generating plants to the end users. To maintain stability in a power system it is urgent that any fault in the transmission system be identified by protective relays and the faulted line be isolated from the network with minimal delay.

This thesis presents a protection scheme used for classification of faults on the series compensated transmission line using Support Vector Machine (SVM). The fault classification task is divided into four separate subtasks ( $SVM_a$ ,  $SVM_b$ ,  $SVM_c$  and  $SVM_g$ ), where the state of each phase and ground is determined by an individual SVM. The network for each phase is supplied by its respective current samples or voltage and current samples, whereas the decision of ground network is based only on the ground current.

The proposed technique has been trained and tested through computer simulation studies for a typical two machine power system model implemented in PSCAD/EMTDC package. The sampling rate is 20 samples per cycle of power frequency. The proposed method uses postfault half cycle (ten samples) for fault classification. The SVMs are trained with different kernel functions with different parameter values to get the most optimized model. Simulation studies have been considered for different operating conditions, including wide variations of load angle, fault inception angle, fault resistance and fault location.

The performance of the proposed method is investigated using the computer simulation which does not exactly match the field data. This is because the incoming data will be affected by the transducers and environmental noise. Therefore, the proposed technique is also tested

with superimposed noise test data. This ensures robustness of the proposed SVM algorithm.

In addition to series compensated transmission line protection studies, the thesis also includes fault analysis of high voltage transmission line without compensation.

The results presented in this thesis confirm the feasibility of the proposed protection scheme.

**Keywords:** Distance protection, Fault classification, Overcurrent protection, Series compensated transmission line, Support vector machine.

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## LIST OF ABBREVIATIONS

<b>ADC</b>	Analog-to-Digital Converter
<b>AI</b>	Artificial Intelligence
<b>ANN</b>	Artificial Neural Network
<b>BPNN</b>	Back Propagation Neural Network
<b>CPNN</b>	Counter Propagation Neural Network
<b>CT</b>	Current Transformer
<b>DC</b>	Direct Current
<b>EHV</b>	Extra High Voltage
<b>EMI</b>	Electromagnetic Interference
<b>ERM</b>	Empirical Risk Minimization
<b>FMNN</b>	Feature Map Neural Network
<b>FNN</b>	Fuzzy Neural Network
<b>GANN</b>	Genetic Algorithm Neural Network
<b>HV</b>	High Voltage
<b>MOV</b>	Metal Oxide Varistor
<b>PT</b>	Potential Transformer
<b>QP</b>	Quadratic Programming
<b>RBF</b>	Radial Basis Function
<b>RBFNN</b>	Radial Basis Function Neural Network
<b>SLT</b>	Statistical Learning Theory
<b>SRM</b>	Structural Risk Minimization
<b>SSR</b>	Subsynchronous Resonance
<b>SVM</b>	Support Vector Machine
<b>ZnO</b>	Zinc Oxide

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