PHD

A Novel Current Based Faulted Phase Selection and Fault Detection Technique for EHV Transmission Systems with some Penetration of Wind Generation

Chen, Jianyi

Award date: 2015

Awarding institution: University of Bath

Link to publication
A Novel Current Based Faulted Phase Selection and Fault Detection Technique for EHV Transmission Systems with some Penetration of Wind Generation

By

Jianyi Chen

Thesis submitted for the degree of

Doctor of Philosophy

Department of Electronic and Electrical Engineering
University of Bath
September 2015

-COPYRIGHT-

Attention is drawn to the fact that copyright of this thesis rests with its author. A copy of this thesis has been supplied on condition that anyone who consults it is understood to recognise that its copyright rests with the author and they must not copy it or use material from it except as permitted by law or with the consent of the author.

This thesis may be made available for consultation within the University Library and may be photocopied or lent to other libraries for the purposes of consultation.
Abstract

In recent years, the capacity of electrical power systems (EPS) has been growing in order to match an increasing demand for electrical power. The expanding power source especially the penetration of the renewable energy makes the systems more difficult to manage and operate. Thus the task of protecting these systems especially for the extra-high-voltage (EHV) transmission line can no longer be handled using the traditional protection schemes, which were designed for simple power system configurations and therefore are not suitable for modern power systems. Also, the protection of EHV transmission line should take into account the increasing penetration of renewable energy generation such as wind farms and the effects of such generations on protection schemes.

This thesis describes a novel phase selection and fault detection scheme using current signal data from one end only of a typical UK 400kV transmission system. Firstly, the measured current signals are decomposed using the wavelet transform to obtain the necessary frequency details and then the spectral energy for a chosen number of wavelet coefficients are calculated using a moving short time window; this forms the feature extraction stage, which in turn, defines the inputs for the artificial neural network which is used for classifying the types of fault. After the fault type is identified, the proposed scheme selects the specific neural network of the fault type to distinguish between internal and external faults by utilizing the same patterns features extracted from the previous stage. The input features comprise both the high and low frequency components to enhance the performance of the scheme. An extensive series of studies for a whole variety of different system and fault conditions clearly show that the performance of the scheme both for phase selection and detection is accurate and robust.

For testing the robustness of the scheme and also as this research project is a UK-China jointly funded EPSRC project, this designed scheme is also applied to a typical 500kV Chinese transmission system with only traditional power generations and with both traditional and renewable generations (wind farms). The effect of the penetration of wind farms on the performance of the proposed protection scheme is
thus investigated. For both systems, promising results from the new protection scheme for the phase selection and fault detection are achieved.
Acknowledgements

I sincerely appreciate the continuous guidance and help from my supervisor Prof. Raj K. Aggarwal. I am very grateful for his critical inputs in many parts of my PhD project. He is always being there to answer my questions and very thoughtful for my study. He shared with me of his invaluable research experience, which is life-long beneficial.

Many thanks to Dr. Simon Le Blond, who shared his valuable experience in the PhD study and the good discussion with him is always helpful and beneficial for my own study. I also would like to thank Dr. Miles Redfern for his help during my PhD course.

I would like to thank Dr. Li Bo, Dr. Chenghong Gu, Dr. Hongbo Liu, Mr. Fan Yi, Dr Chenchen Yuan, Dr. Zhimin Wang for their willingness to share knowledge and participation in quality technical discussions with me. I am especially grateful to Dr. Zechun Hu, for his generous guidance and being supportive.

I would like to express my gratefulness to my best friends Dr. Zhang Yan and Dr. Shuang Yu, for the warmest friendship for me in my daily life.

From a more personal aspect, special thanks to all my family and especially my parents and my husband, for being always supportive for my PhD study.
# Contents

Abstract ........................................................................................................................................ i

Contents ...................................................................................................................................... iv

Index to Figures ........................................................................................................................... x

Index to Tables ............................................................................................................................. xix

List of Abbreviations .................................................................................................................... xx

List of Symbols .............................................................................................................................. xxii

Chapter 1  Introduction ................................................................................................................... 1

1.1 EHV transmission line protection ......................................................................................... 1

1.2 Opportunities for Fault Transients Based protection ......................................................... 2

1.3 Motivation of this study ......................................................................................................... 5

1.4 Objectives of the project ........................................................................................................ 6

1.5 Scope of the thesis .................................................................................................................. 7

Chapter 2  Principles of Protection ............................................................................................... 10

2.1 Introduction ........................................................................................................................... 10

2.2 Faults ...................................................................................................................................... 10

2.2.1 Reasons for faults .............................................................................................................. 10

2.2.2 Fault types ........................................................................................................................ 11

2.2.3 Influence of faults ............................................................................................................. 14

2.3 Fundamentals of Protection .................................................................................................... 14

2.3.1 Qualities required of protection ....................................................................................... 15
2.3.2 Traditional Protection Principles .................................................. 15

2.3.3 Transients Based Protection ......................................................... 17

2.4 Simulation and Analysing Tools ...................................................... 18

2.4.1 Power System Simulation - EMTP and MATLAB Simulink .............. 18

2.4.2 Feature Extraction – The Wavelet Transform ................................ 19

2.4.3 Pattern Recognition – The Neural Network .................................. 21

2.5 Summary ....................................................................................... 22

Chapter 3 Literature Review on Transients Based Protection .................. 23

3.1 Introduction .................................................................................... 23

3.2 Transients Based Protection (TBP) .................................................. 23

3.3 Unit TBP using the wavelet transform (WT) ...................................... 24

3.4 Non-unit TBP scheme .................................................................... 25

3.5 Transients Based Phase Selection Schemes ...................................... 26

3.6 Summary ....................................................................................... 28

Chapter 4 System Simulation and Signal Analysis Method for Fault Generated Transients ............................................................... 30

4.1 Fault transients detection based on EMTP ....................................... 30

4.1.1 Simulation Tool - EMTP ............................................................... 30

4.1.2 Electrical Power System Model .................................................. 30

4.1.3 Simulation results ....................................................................... 33

4.2 Fault signal analysis using wavelet transform ................................... 46
4.2.1 Wavelet and Wavelet Transform .............................................. 46

4.2.2 WT Results for Different Fault Conditions............................... 57

4.3 Summary ................................................................................. 66

Chapter 5 Artificial Intelligence Techniques and the Development of the Phase
Selection Scheme ........................................................................ 68

5.1 Introduction ........................................................................... 68

5.2 Motivation to use AI techniques .............................................. 68

5.3 AI Techniques Introduction.................................................... 69

5.3.1 Fuzzy logic ........................................................................ 69

5.3.2 Artificial Neural Networks (ANN) .......................................... 71

5.4 FL and ANN based Phase Selection scheme............................... 76

5.4.1 Overview ........................................................................... 76

5.4.2 The selection of Detail energy .............................................. 77

5.4.3 Fuzzy Logic Application....................................................... 78

5.4.4 Neural Network Architecture and Training ......................... 81

5.5 Results and Discussion............................................................ 83

5.6 Summary ................................................................................. 86

Chapter 6 Current Based Phase Selection and Fault Detection Scheme and Case
Studies on UK 400kV EHV Transmission Line .................................. 87

6.1 Introduction ........................................................................... 87

6.2 System Model and Fault Simulation ......................................... 87

6.3 Implementation of the Protection Scheme ................................. 88
6.3.1 Overview .................................................................................. 88
6.3.2 Feature Extraction ....................................................................... 89
6.3.3 ANN Architecture and Training .................................................. 94
6.4 Results and Discussion ..................................................................... 101
6.4.1 Phase Selection Results and Discussions ..................................... 101
6.4.2 Fault Detection Results and Discussions ...................................... 104
6.5 Summary ......................................................................................... 111

Chapter 7 Current Based Phase Selection and Fault Detection Scheme
Application and Case Studies on Chinese 500kV EHV Transmission Line ............. 113
7.1 Introduction ..................................................................................... 113
7.2 System Model and Fault Simulation for the typical 500kV China
transmission line .................................................................................. 113
7.2.1 System Description ....................................................................... 113
7.2.2 Simulation Results .......................................................................... 115
7.3 Implementation of the Protection Scheme ......................................... 117
7.3.1 Overview ...................................................................................... 117
7.3.2 Feature Extraction ......................................................................... 117
7.3.3 ANN Architecture and Training .................................................. 124
7.4 Results and Discussions ..................................................................... 125
7.4.1 Phase Selection Results and Discussions ..................................... 125
7.4.2 Fault Detection Results and Discussions ...................................... 131
7.5 Summary ......................................................................................... 138
Chapter 8  Current Based Phase Selection and Fault Detection Scheme Application and Case Studies on Chinese 500kV EHV Transmission Line with Both Traditional Generation and Wind Generation

8.1  Introduction .................................................................................................................. 140

8.1.1  Wind Power .............................................................................................................. 140

8.1.2  Possible Impact ........................................................................................................ 142

8.1.3  Different Types of Wind Turbines ........................................................................... 142

8.2  System Model and Fault Simulation ............................................................................. 143

8.2.1  System with wind farm penetration ....................................................................... 143

8.2.2  Simulation Results .................................................................................................. 144

8.3  Implementation of the Protection Scheme .................................................................... 147

8.3.1  Feature Extraction ................................................................................................... 147

8.3.2  ANN Architecture and Training ............................................................................. 153

8.4  Results and Discussions ............................................................................................. 154

8.4.1  Phase Selection Results .......................................................................................... 154

8.4.2  Fault Detection Results .......................................................................................... 159

8.5  Summary ....................................................................................................................... 166

Chapter 9  Conclusions and Outlook .................................................................................. 167

9.1  Introduction .................................................................................................................. 167

9.2  Review of Major Findings and Achievements .............................................................. 167

9.3  Future Work ................................................................................................................ 170

Literatures .......................................................................................................................... 172

viii
Appendix A ............................................................................................................................................................................. 178

Appendix B ............................................................................................................................................................................. 181

Related Publications .................................................................................................................................................................. 185
Index to Figures

Figure 1-1 Electrical Power System Structure[3] .............................................. 1

Figure 2-1 Causes of overhead-line faults, British system 66kV and above[1] .... 11

Figure 2-2 Single phase to ground [19]................................................................. 12

Figure 2-3 double phase to ground [19]................................................................. 12

Figure 2-4 Phase to Phase fault[19] ................................................................. 13

Figure 2-5 three phase to ground fault[19] ............................................................ 13

Figure 2-6 A typical mother wavelet [34].............................................................. 20

Figure 4-1 The EMTP model for the UK 400kV EHV power transmission system 33

Figure 4-2 Fault current waveforms for AG fault, 32km, 90° ............................ 35

Figure 4-3 Fault current waveforms for AB fault, 32km, 90° ............................ 36

Figure 4-4 Fault current waveform of ABG fault, 32km ................................. 37

Figure 4-5 Fault current waveform for ABCG fault, 32km ......................... 38

Figure 4-6 Typical voltage wave for each phase .............................................. 39

Figure 4-7 Phasor diagram for three types of faults (a) AB (b) BC (c) CA ...... 40

Figure 4-8 Fault current waveform for AG fault, 32km, 0° .............................. 40

Figure 4-9 Fault current waveform for AB fault, 32km, 0° .............................. 41

Figure 4-10 Power Transmission line model ...................................................... 42

Figure 4-11 Current waveform of AG fault, 90°, left - 8km, right - 56km .......... 43

Figure 4-12 Current waveform of AG fault, 90°, left - 88km, right - 120km .... 43

Figure 4-13 Current waveform of AB fault, 90°, left - 8km, right - 56km ......... 44
Figure 4-14 Current waveform of AB fault, 90°, left - 88km, right - 120km........... 44
Figure 4-15 Current waveform of ABG fault, left - 8km, right - 56km.................. 44
Figure 4-16 Current waveform of ABG fault, left - 88km, right - 120km............. 45
Figure 4-17 Current waveform of ABCG fault, left - 8km, right - 56km............. 45
Figure 4-18 Current waveform of ABCG fault, left - 88km, right - 120km........... 45
Figure 4-19 Sine Wave and db10 Wavelet[32].......................................................... 47
Figure 4-20 Haar Wavelet...................................................................................... 48
Figure 4-21 Daubechies wavelets family [32]......................................................... 49
Figure 4-22 High scale and low scale components of the wavelets [26]............. 50
Figure 4-23 Filtering process [26]........................................................................... 51
Figure 4-24 One-level WT Decomposition [26]....................................................... 51
Figure 4-25 Wavelet decomposition tree [26].......................................................... 52
Figure 4-26 Decomposition of the current signal using wavelet analysis .......... 53
Figure 4-27 Fault Current Signal Decomposition by Db1 to Db10......................... 56
Figure 4-28 4-level WT decomposition of the fault current signals AG fault, 16km, 90° .................................................................................................................. 59
Figure 4-29 Spectral Energy variation with time for the 4-level WT decomposition of the fault current signals AG fault, 16km, 90° ......................................................... 60
Figure 4-30 Spectral Energy variation with time for the 4-level WT decomposition of the fault current signals AB fault, 16km, 90° ......................................................... 60
Figure 4-31 Spectral Energy variation with time for the 4-level WT decomposition of the fault current signals ABG fault, 16km .................................................... 61
Figure 4-32 Spectral Energy variation with time for the 4-level WT decomposition of the fault current signals ABCG fault, 16km

Figure 4-33 Energy variation with time for the 4-level WT decomposition of the fault current signals AG fault, 16km, 0°

Figure 4-34 Spectral Energy variation with time for the 4-level WT decomposition of the fault current signals BG fault, 16km, 90°

Figure 4-35 Spectral Energy variation with time for the 4-level WT decomposition of the fault current signals BG fault, 64km, 90°

Figure 4-36 Spectral Energy variation with time for the 4-level WT decomposition of the fault current signals BG fault, 120km, 90°

Figure 5-1 Example of S-shaped membership function [26]

Figure 5-2 Simplified Neuron model [18]

Figure 5-3 Three types of activation function [18]

Figure 5-4 Working principle of artificial neural network [18]

Figure 5-5 NN-topology for a three layer feedforward network [18]

Figure 5-6 Flow Chart for FL and ANN based Phase Selection Scheme

Figure 5-7 Comparison of spectral energy and fuzzificated data of A phase for AG fault at 32km (fault inception angle=90° and 0°)

Figure 5-8 Comparison of spectral energy and fuzzificated data of B phase for AG fault at 32km (fault inception angle=90° and 0°)

Figure 5-9 Comparison of spectral energy and fuzzificated data of C phase for AG fault at 32km (fault inception angle=90° and 0°)

Figure 5-10 NN-topology for this problem

Figure 5-11  MSE variation for the Training of an ANN
Figure 5-12 Actual output of ANN for test data of AG fault at 32km (fault inception angle=90°) ................................................................. 84

Figure 5-13 Actual output of ANN for test data of AG fault at 32km (fault inception angle=0°) ................................................................. 84

Figure 6-1 Power system model ........................................................................... 88

Figure 6-2 The Protection Scheme Framework .......................................................... 89

Figure 6-3 Three phase current waveforms of an AG fault at 64 km from the sending end (fault inception angle 90°) ........................................... 92

Figure 6-4 Ten level spectral energy details of the three phase Current of an AG fault at 64 km from the sending end (fault inception angle 90°) ................. 93

Figure 6-5 Ten level spectral energy details of the A phase of an AG fault at 64 km from the sending end (fault inception angle 90° and 0°) ............................... 93

Figure 6-6 Ten level spectral energy details of the A phase of an AG fault for internal fault 8km from the sending end and external faults (fault inception angle 90°) ......................................................................................... 94

Figure 6-7 ANN-topology for the Phase Selection Scheme ................................. 96

Figure 6-8 Example of inputs: Accumulated Energy of D₁ of phase A for AG fault at 64km from the sending end, 90° fault .......................................................... 97

Figure 6-9 Example of target outputs: for AG fault at 64km from the sending end, 90° fault .......................................................... 97

Figure 6-10 ANN-topology for Fault Detection .................................................. 98

Figure 6-11 Example of Inputs: Accumulated Energy of D₁ of phase A for AG internal fault at 48km from the sending end, 90° .................................................. 99

Figure 6-12 Example of target outputs: for AG internal fault .......................... 100
Figure 6-13 Example of Inputs: Accumulated Energy of D₁ of phase A for AG external fault at the sending end, 90° ................................................................. 100

Figure 6-14 Example of target outputs: for AG external fault ......................... 100

Figure 6-15 ANN actual output for AC fault at 116km, 90° ............................. 101

Figure 6-16 ANN outputs of AG faults (fault inception angle 90°) .................. 106

Figure 6-17 ANN outputs of BG faults ............................................................ 107

Figure 6-18 ANN outputs of Faults at 72km (fault inception angle 90°) .......... 108

Figure 6-19 ANN outputs of AG faults (fault inception angle 90°) ............... 109

Figure 6-20 ANN outputs of AB phase faults (fault inception angle 90°) ....... 109

Figure 6-21 ANN outputs of ACG faults .......................................................... 110

Figure 6-22 ANN outputs of ABCG faults ....................................................... 110

Figure 6-23 ANN outputs of AG faults for sending end source capacity of 35 GVA ............................................................................................................ 111

Figure 7-1 Schematic of the model for the China 500kV Transmission System.... 114

Figure 7-2 500kV China Power system model in MATLAB Simulink ............ 114

Figure 7-3 Fault Current Signal for the 32km AG fault of the China 500kV system, 90° ........................................................................................................ 116

Figure 7-4 Fault Current Signal for the 32km AG fault of the UK 400kV system, 90° ........................................................................................................ 116

Figure 7-5 Accumulated Energy of WT ten level details for the AG fault at 32km (90°) from the China 500kV system .................................................. 118

Figure 7-6 Accumulated Energy of WT ten level details for the AG fault at 100km (90°) from the China 500kV system .................................................. 119
Figure 7-7 Accumulated Energy of WT ten level details for the AC fault at 100km (90°) from the China 500kV system ............................................................................................................. 119

Figure 7-8 Accumulated Energy of WT ten level details for the ACG fault at 100km from the China 500kV system ............................................................................................................. 120

Figure 7-9 Accumulated Energy of WT ten level details for the ABCG fault at 100km from the China 500kV system ............................................................................................................. 120

Figure 7-10 Accumulated Energy of WT ten level details for the AG fault at 20km (90° and 0°) from the China 500kV system ............................................................................................................. 121

Figure 7-11 Accumulated Energy of WT ten level details for the CG fault at 20km (90°) from the China 500kV system ............................................................................................................. 122

Figure 7-12 Accumulated Energy of WT ten level details for the CG fault at 60km (90°) from the China 500kV system ............................................................................................................. 122

Figure 7-13 Accumulated Energy of WT ten level details for the CG fault at 180km (90°) from the China 500kV system ............................................................................................................. 123

Figure 7-14 Accumulated Energy of WT ten level details for the CG fault at 280km (90°) from the China 500kV system ............................................................................................................. 123

Figure 7-15 Phase Selection Results for the ABG fault at 50km from the China 500kV system ................................................................................................................................. 125

Figure 7-16 Phase Selection Results for the AC fault at 50km (90°) from the China 500kV system ................................................................................................................................. 127

Figure 7-17 Phase Selection Results for the AC fault at 50km (0°) from the China 500kV system ................................................................................................................................. 127

Figure 7-18 Phase Selection Results for the BCG fault at 50km from the China 500kV system ................................................................................................................................. 129

Figure 7-19 Phase Selection Results for the BC fault at 50km 90° from the China 500kV system ................................................................................................................................. 130
Figure 7-20 Phase Selection Results for the BG fault at 50km 90° from the China 500kV system

Figure 7-21 ANN outputs of AG faults (fault inception angle 90°)

Figure 7-22 ANN outputs of AG faults at 275km - internal fault

Figure 7-23 ANN outputs of AG faults at the sending end – external fault

Figure 7-24 ANN outputs of AG faults at the receiving end – external fault

Figure 7-25 ANN outputs of faults at 145km – internal fault

Figure 7-26 ANN outputs of faults at sending end - external fault

Figure 7-27 ANN outputs of the AG fault close to busbar

Figure 7-28 ANN outputs of ACG faults close to busbar

Figure 7-29 ANN outputs of ABCG faults close to busbar

Figure 8-1 Wind Turbine Farms in Germany

Figure 8-2 Worldwide Wind Power Capacity in 2012 [67]

Figure 8-3 DFIG topologies [66]

Figure 8-4 Power System Model with Wind Farm Penetration in Simulink

Figure 8-5 Fault Current signals in the system for an AG fault at 20km, 90°

Figure 8-6 Fault Current signals in the system for an AG fault at 280km, 90°

Figure 8-7 Accumlated Energy of WT ten level details for the AG fault at 0km (90°), only for phase A

Figure 8-8 Accumlated Energy of WT ten level details for the AG fault at 180km (90°), only for phase A
Figure 8-9 Accumlated Energy of WT ten level details for the AG fault at 270km (90°), only for phase A

Figure 8-10 Accumlated Energy of WT ten level details for the AG fault at 270km (90°), with the wind farm

Figure 8-11 Accumlated Energy of WT ten level details for the AG fault at 160km (90°), only for phase A

Figure 8-12 Accumlated Energy of WT ten level details for the AG fault at 160km (0°), only for phase A

Figure 8-13 Accumlated Energy of WT ten level details for the AB fault at 160km (90°)

Figure 8-14 Accumlated Energy of WT ten level details for the ACG fault at 160km

Figure 8-15 Accumlated Energy of WT ten level details for the ABCG fault at 160km

Figure 8-16 Phase Selection Results for the ACG fault at 50km

Figure 8-17 Phase Selection Results for the CG Fault at 150km (90°)

Figure 8-18 Phase Selection Results for the CG Fault at 150km (0°)

Figure 8-19 Phase Selection Results for the AG Fault at 50km (90°)

Figure 8-20 Phase Selection Results for the BCG Fault at 50km

Figure 8-21 ANN Outputs of AB Faults (Fault Inception Angle 90°) (a) 150km internal fault (b) external fault at sending end (c) external fault at receiving end

Figure 8-22 ANN Outputs of the AG Fault (Fault Inception Angle 90°) (a) 150km internal fault (b) external fault at sending end (c) external fault at receiving end
Figure 8-23 ANN Outputs of AG Fault (Fault Inception Angle 0°) (a) 150km internal fault (b) external fault at sending end (c) external fault at receiving end ............ 161

Figure 8-24 ANN Outputs of the Internal Faults at 150km (a) AG (90°) (b) AB (90°) (c) ACG (d) ABCG ................................................................. 162

Figure 8-25 ANN Outputs of the External Faults at Sending End (a) AG (90°) (b) AB (90°) (c) ACG (d) ABCG ................................................................. 163

Figure 8-26 ANN Outputs of the External Faults at the Receiving End (a) AG (90°) (b) AB (90°) (c) ACG (d) ABCG ................................................................. 163

Figure 8-27 ANN Outputs of AG Internal Faults (Fault Inception Angle 90°) (a) 40km (b) 150km (c) 260km ................................................................. 164

Figure 8-28 ANN Outputs of the AG Fault Close to Busbar (a) 0km 90° (b) sending end 90° (c) 300km 90° (d) receiving end 90° ................................................................. 165

Figure 8-29 ANN Outputs of the ABCG Fault Close to Busbar (a) 0km (b) sending end (c) 300km (d) receiving end ................................................................. 165
Index to Tables

Table 4-1 Parameters of Source Side Networks ......................................................... 32
Table 4-2 Parameters of Transmission Line [50] .......................................................... 32
Table 4-3 Details and the Frequency information .......................................................... 52
Table 5-1 Activation Functions [18] ........................................................................... 72
Table 5-2 Typical faults target output representations ............................................... 81
Table 5-3 Test results of neural network .................................................................... 85
Table 6-1 Ten Fault Types and the Target Outputs .................................................... 96
Table 6-2 Fault type examples .................................................................................... 99
Table 6-3 Results for various fault positions (Fault inception angle: 0° for CG and BC fault) ................................................................................................................. 102
Table 6-4 Results for various fault inception angle (Fault location: 116km) ............ 103
Table 6-5 Results for various fault types (Fault inception angle: 0° and fault location: 72km) ................................................................................................................. 104
Table 7-1 Set-up for the transmission line block in Simulink [65] ............................ 115
Table 7-2 Results for Various Fault Locations (Fault inception angle: 90°) ......... 126
Table 7-3 Results for various fault inception angles (Fault location: 150km) ...... 128
Table 7-4 Results for various fault types ................................................................. 131
Table 8-1 Results for Various Fault Locations (Fault Inception angle: 90°) .......... 155
Table 8-2 Results for Various Fault Inception Angle (Fault Location: 150km) ...... 157
Table 8-3 Results for Various Fault Types ............................................................... 159
**List of Abbreviations**

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AC</td>
<td>Alternating current</td>
</tr>
<tr>
<td>AG</td>
<td>A phase to ground fault</td>
</tr>
<tr>
<td>AB</td>
<td>A phase to B phase fault</td>
</tr>
<tr>
<td>ABCG</td>
<td>Three-phase to ground fault</td>
</tr>
<tr>
<td>ABG</td>
<td>A to B phase to ground fault</td>
</tr>
<tr>
<td>AI</td>
<td>artificial intelligence</td>
</tr>
<tr>
<td>ANN</td>
<td>artificial neural network</td>
</tr>
<tr>
<td>ATP</td>
<td>Alternative Transients Program</td>
</tr>
<tr>
<td>BG</td>
<td>B phase to ground fault</td>
</tr>
<tr>
<td>BC</td>
<td>B phase to C phase fault</td>
</tr>
<tr>
<td>BCG</td>
<td>B to C phase to ground fault</td>
</tr>
<tr>
<td>CA</td>
<td>C phase to A phase fault</td>
</tr>
<tr>
<td>CAG</td>
<td>C to a phase to ground fault</td>
</tr>
<tr>
<td>CG</td>
<td>C phase to ground fault</td>
</tr>
<tr>
<td>CT</td>
<td>Current Transformer</td>
</tr>
<tr>
<td>CVT</td>
<td>Capacitor Voltage Transformer</td>
</tr>
<tr>
<td>DbN</td>
<td>Daubechies wavelets N</td>
</tr>
<tr>
<td>DFIG</td>
<td>Double Fed Induction Generator</td>
</tr>
<tr>
<td>DWT</td>
<td>Discrete Wavelet Transform</td>
</tr>
<tr>
<td>EHV</td>
<td>Extra-High Voltage</td>
</tr>
</tbody>
</table>

xx
<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>EMTP</td>
<td>Electromagnetic Transients Program</td>
</tr>
<tr>
<td>EPS</td>
<td>Electrical Power System</td>
</tr>
<tr>
<td>FL</td>
<td>Fuzzy Logic</td>
</tr>
<tr>
<td>FT</td>
<td>Fourier Transform</td>
</tr>
<tr>
<td>FFT</td>
<td>Fast Fourier Transform</td>
</tr>
<tr>
<td>HF</td>
<td>High Frequency</td>
</tr>
<tr>
<td>LF</td>
<td>Low Frequency</td>
</tr>
<tr>
<td>MATLAB</td>
<td>Matrix Laboratory - Name of software</td>
</tr>
<tr>
<td>TBP</td>
<td>Transient Based Protection</td>
</tr>
<tr>
<td>WT</td>
<td>Wavelet Transform</td>
</tr>
</tbody>
</table>
## List of Symbols

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>kV</td>
<td>Kilo Volts</td>
</tr>
<tr>
<td>MW</td>
<td>Mega Watts</td>
</tr>
<tr>
<td>km</td>
<td>Kilo Metres</td>
</tr>
<tr>
<td>kHz</td>
<td>Kilo Hertz</td>
</tr>
<tr>
<td>Ω</td>
<td>ohms</td>
</tr>
<tr>
<td>V</td>
<td>Voltage, Volts</td>
</tr>
<tr>
<td>I</td>
<td>Current</td>
</tr>
<tr>
<td>$I_A, I_B, I_C$</td>
<td>phase A, B and C current</td>
</tr>
<tr>
<td>$V_A, V_B, V_C$</td>
<td>phase A, B and C voltage</td>
</tr>
<tr>
<td>$\theta_A, \theta_B, \theta_C$</td>
<td>phase A, B and C phase angle</td>
</tr>
<tr>
<td>t</td>
<td>time</td>
</tr>
<tr>
<td>cD</td>
<td>Wavelet coefficients for the details</td>
</tr>
<tr>
<td>cA</td>
<td>Wavelet coefficients for the approximations</td>
</tr>
<tr>
<td>cD_N</td>
<td>Level N wavelet coefficients for the details</td>
</tr>
<tr>
<td>cA_N</td>
<td>Level N wavelet coefficients for the approximations</td>
</tr>
<tr>
<td>E</td>
<td>Spectral energy of the wavelet coefficients</td>
</tr>
<tr>
<td>P</td>
<td>Power</td>
</tr>
<tr>
<td>S</td>
<td>Signal</td>
</tr>
<tr>
<td>D</td>
<td>Wavelet Details</td>
</tr>
<tr>
<td>A</td>
<td>Wavelet Approximation</td>
</tr>
</tbody>
</table>
\( A_N \) Level N approximation in wavelet decomposition

\( D_N \) Level N details in wavelet decomposition

\( R \) Resistance

\( L \) Inductance

\( C \) Capacitance

\( X \) Inductive reactance

\( Z \) Impedance

\( \psi(t) \) Mother Wavelet Function

\( x_p \) Neural network input

\( y_p \) Neural network output

\( w_p \) Weighting factor for the neurons

\( f(x) \) function
Chapter 1 Introduction

With the increasing complexity and continuous expansion of power transmission systems, especially the introduction of renewable energy plants like wind farms, the protection of such systems face more challenges. Conventional power protections can have setting problems caused by power flow changes due to wind generations; also, they can have mal-operations caused by power swings. As a result, new protection schemes are desired. They should not only have high reliability and accuracy, but also have good adaptability so that they are capable of handling various system conditions. It is the objective of this study to propose and demonstrate one such a protection scheme for modern power transmission systems and this chapter will focus on the background and how it leads to the scheme studied in this work.

1.1 EHV transmission line protection

An electrical power system consists of three parts: generation, transmission and distribution of electrical power, as shown in Figure 1-1. Transmission lines are used to deliver bulk electrical power from generations to distribution networks where power is distributed to various consumers[1]. The voltage of transmission line 220kV or above is defined as Extra-High Voltage (EHV) in most countries. In the UK, the EHV levels are 275kV and 400kV[1], while they are 330kV, 500kV and 750kV in China[2]. The EHV transmission line forms the backbone for power delivery from generating plants to users; therefore, its safety is critical to power grids’ performance.

Figure 1-1 Electrical Power System Structure[3]
Most of the EHV transmission lines are overhead lines and they are exposed to the natural environment, which is the major reason for the occurrence of faults due to lighting, wind, snow, fog, animals etc. For instance, a lightning strike near or on the line can cause a short circuit fault on the transmission line. When the fault happens, the line is interrupted and a large amount of fault current which can be orders of magnitude higher than the normal operating current of the system will occur. This poses a big threat to power system stability and electrical equipment as these are designed based on the normal operating current. In the worst cases, the equipment of the power system could be damaged permanently. To prevent these from happening, faults occurring on the EHV transmission line must be detected and cleared as quickly as possible[1].

Hence, a reliable and fast response EHV transmission protection scheme is essential for the safety of power grids. Ideally, it should be able to classify and detect all types of faults in the minimum amount of time.

1.2 Opportunities for Fault Transients Based protection

Traditional transmission protection schemes have several protection principles, e.g. overcurrent, current differential and distance protection. These protection schemes can be divided into two categories: non-unit and unit protection, the latter being based on using communication links. The widely used non-unit protection is distance protection which is based on the measuring of impedance. It is fast and simple, but can only protect 80% of transmission line and is vulnerable to power swing which is due to loss of load or generations. A typical unit protection scheme is the current differential scheme, which is based on the difference of currents at the two ends of a transmission line during a fault. Such a scheme requires communication links, and also the reliability of the links will bring further uncertainty to the scheme. Therefore, a protection scheme that can protect the whole transmission line without communication links would be a preferable choice[4].

All traditional protection principles have one thing in common: they are based on the measurement of power frequency components to detect faults; hence, their accuracy and reliability are vulnerable to the disturbance related to the power frequency
associated with power swings; sudden changes in voltage and currents are called power swings, which are normally caused by line switching, generation disconnected, loss or application of large load, etc. They might trigger a false fault alarm, which will lead to unnecessary reaction of the relay trip[5].

Furthermore, as nowadays the requirement to utilize green power resource to reduce carbon dioxide emission becomes a major preference of the mainstream society, for transmission systems a significant challenge is the increasing penetration of green energy plants into power grids, such as wind farms. The penetration of wind farms makes the protection of transmission line systems even more complex. The reasons are:

- Wind farms have impact on power flow and this can cause setting problems for traditional protection schemes.
- Wind farms normally use additional power electronics for power conversion associated with the most widely used wind generator - the Double Fed Induction Generator (DFIG). These electronic circuits will affect significantly the performance of traditional power frequency signals based protection schemes [6].

In this context, a protection principle involving fundamental changes which can tackle the issues aforementioned is necessary to improve the security of the increasingly complex transmission system.

Generally speaking, when a fault occurs on a transmission line, not just the fundamental power component will be affected, but some transients associated with the fault will also be produced. The frequency of these transients range from DC to several kHz and these wide bandwidth frequency components are usually treated as noise in traditional protection schemes to ensure the precision. Due to the encountered problems of traditional protection schemes, scholars started to research into the higher frequency signals and found these transients are related to power system topology and faults’ characteristics. Moreover, in fault transients, there is extensive useful information that, if appropriately post-processed and extracted, can
help effectively and efficiently identify fault types, fault positions, etc. and has the potential of solving the problem related to the use of power frequency signals.

Depending on the type of protection technique, transmission line protection performs two important functions: 1) faulted phase(s) selection: classify the types of fault, e.g., single phase to ground faults, phase to phase faults, etc. In this work, based on faulted phase selection, the protection scheme can select different fault detection networks (within the overall scheme) to deal with different fault types. 2) fault detection: discriminate the internal faults (fault occurring inside the transmission line) from the external faults (fault occurring outside the transmission line) so that only the faulted line will be disconnected. The performance of these two functions is crucial for reducing the impact of faults on power system stability and damage to expensive part of equipment[7].

The high frequency components caused by fault occurrence is usually removed for traditional phase selection schemes as they are based on power frequency components. In fact, the information contained in the frequency components can potentially be used to realize the phase selection as part of a protection scheme[8]. In [8], the authors have developed a faulted phase selection based on fault generated high frequency voltage components and the artificial neural network (ANN) technique. In [9] and [10], phase selector based on the Wavelet Transform (WT) employed to extract the characteristics of the transient signals was proposed. In [11] and [12], the combination of the WT and the ANN was used in the development of a phase selector. A major limitation of the aforementioned technique based on high frequency signals is the limited bandwidth associated with the capacitor voltage transformers (CVT) which severely attenuate the frequency components above about 1 kHz due to it is capacitive in nature. As a direct consequence, the accuracy and robustness of the technique is compromised.

In [13], the author presents a new non-communication protection scheme for discriminating internal and external faults for a whole variety of different system and fault conditions and make use of the fault generated high frequency current signals. Although the results presented demonstrate a good performance, the technique developed is heavily dependent on an accurate design of multi-channel digital filters.
Reference [14] is also based on utilising fault generated current signals only, but this technique only determines the direction of a fault (forward or reverse) and therefore requires a communication channel for accurately detecting an internal fault. In [4], the authors have introduced an approach based on WT and ANN to classify internal and external faults using voltage signals. However, again, due to the CVT bandwidth limitation, the high frequencies associated with the voltage need to be obtained by additional devices such as specially designed high frequency voltage detectors. In contrast, the relays designed based only on current transients are more practical and well suited in making use of high frequency in current signals by virtue of the wide bandwidth (70 kHz) of current transformers (CT).

With the developments of the microprocessor technique in modern times, the fault-transient signals can be properly captured and sampled, which makes their utilization realistic. As a result, fault transients were used to develop new protection principles and these principles are all classified as ‘Transients Based protection’ (TBP) [15].

1.3 Motivation of this study

Non-unit TBP scheme that can protect the whole transmission line and is based on voltage transients was developed [16, 17].

The first step for TBP schemes is usually the feature extraction stage, i.e. to capture the fault transients from the signals for further analysis and post-processing. For example, WT method, which is a mathematical means to decompose a signal, has strong ability of capturing the characteristics of the signal components in different frequency bands at the same time retaining the time domain information[4]. Therefore it can be used as feature extraction tool for the raw fault generated signals in power protection schemes and this is an approach adopted in this work.

As information after the feature extraction stage (e.g., from the wavelet decomposition of the signal) is still complex and large, it is very difficult to design well defined theoretical methods to deal with them and make accurate fault decisions. ANN techniques are an alternative way to handle the information. They can learn complex nonlinear relationships under large amount of data and create patterns for
learned relationships. The information in fault transients can then be patterned and used to make decisions about faults[18].

Current TBP schemes have some drawbacks such as using voltage signal measured by CVT which has limited frequency response that will affect the performance of TBP. More details will be provided and analysed in Chapter 3. To tackle the problems, a novel non-unit TBP scheme based on both high and low frequency transients generated by fault from only one end of transmission line will be developed in this work. It will be using the concept of WT for both time and frequency domain decomposition of transient currents and ANNs for the fault decision.

This is an EPSRC funded UK-China jointly research programme. The scheme is first developed based on a typical UK 400 kV EHV transmission system and then applied to a typical China 500kV EHV transmission systems with and without wind power penetrations.

1.4 Objectives of the project

The overall objective of the project is to propose and demonstrate a novel power transmission line protection scheme for EHV transmission lines based on the WT and ANN. The detailed steps and objectives are summarized below:

- Build a model of a typical UK 400kV transmission network as a basis to develop the scheme. Based on the model, different types of the faults (such as phase-ground, phase-to-phase, phase-to-phase-ground and three phase-ground faults) on different position of transmission line are simulated using the EMTP-ATP software. Also, the influence of different fault inception angle of both the phase-ground fault and the phase-to-phase fault on the resultant signal is investigated.
- Use WT to capture the most significant feature information contained in fault transients by decomposing them both in the frequency and time domain. Select levels of WT decomposition components as features for decision making.
• Based on the simulated data from the UK 400 kV transmission line model, use the WT and ANN technique to develop a protection methodology comprised of phase selection and fault detection scheme, which can classify on which phase the fault has occurred and whether a fault is present inside or outside a protected zone. Test and demonstrate the scheme under different fault and system conditions.

• Apply the developed scheme to a typical Chinese EHV power system with traditional generations and then with wind turbine generations. Model two systems - one uses a typical 500kV transmission line with the traditional power generation and the other uses wind farms replacing part of the power generation. Apply the scheme to both systems and compare the performances of the protection scheme on these two systems, so as to demonstrate the robustness and adaptability of the developed scheme.

1.5 Scope of the thesis

This work has 10 chapters. A brief outline of their contents is given below.

Chapter 2

The fundamental knowledge of the protection schemes is demonstrated. WT and ANN techniques, as well as simulation tools such as EMTP and MATLAB are briefly explained.

Chapter 3

A literature review of transient based protection schemes with ANN and WT techniques applied are summarized in this chapter. The advantages and drawbacks of these schemes are stated.

Chapter 4

In the first section of this chapter, the modelling of a typical UK 400kV transmission line based on EMTP is described. The details of the model are listed and simulations of different types of faults are carried out.
In the second section of this chapter, WT is introduced in detail. Why and how it is used for feature extraction is introduced in detail. The decomposition of the fault current signals for different types of faults from the simulation studies in the first section are conducted, demonstrated and compared.

Chapter 5

Artificial intelligence techniques are introduced in detail, with a focus on the Fuzzy Logic and the ANN. Why and how they are used is also discussed. An initial phase selection scheme based on Fuzzy logic and ANN is tested in this chapter.

Chapter 6

The complete power protection scheme is presented in this chapter. The phase selection scheme based on fault current signals using WT and ANN is firstly demonstrated in this chapter. Based on the model described in chapter 4, wavelet toolbox is applied to decompose fault current signals for feature extraction. Then the outputs from the feature extraction stage are taken as inputs for ANN to realise phase selection. The details of the construction of ANN are also introduced.

As the main part of the protection scheme, the fault detection scheme based on WT and ANN is also demonstrated in this chapter.

Chapter 7

A typical 500 kV Chinese transmission system is modelled and the various faults are simulated to provide data to examine the performance of the protection scheme developed in the former chapters. The results are shown and compared.

Chapter 8

The modelling of the China transmission system with wind farm penetration is introduced. Compared to the system in chapter 8, part of the traditional power generation is replaced by a wind farm. The protection scheme is then again applied to this system. The different behaviour of the protection scheme in response to the system changes are analysed and discussed.
Chapter 9

Conclusions are drawn and the possible future work is proposed.
Chapter 2  Principles of Protection

2.1 Introduction

In this chapter, principles of protection are demonstrated. To understand better the principles of power system protection, the faults and their causes and influences are firstly described. Then, the basics of protection schemes are explained, including both the traditional schemes such as the overcurrent protection etc. and also the transients based protection (TBP) scheme employed herein. In the final parts, the tools for realizing the protection scheme proposed in this thesis are briefly introduced.

2.2 Faults

As an electrical power system is comprised of different complex interacting elements, faults always have a possibility of occurrence. A fault is not avoidable, but if an appropriate protection scheme is used, the damage to the power system can be minimised. In three phase circuits of a power system, faults are such that one or several conductors are shorted to each other or to ground in any number of combinations[1]. The different combinations are different types of fault and they can be caused by many various reasons which will be explained in more details in this section.

2.2.1 Reasons for faults

The most common reason that causes faults on a transmission line is due to lightning. Some weather conditions like rain, wind, snow, ice, frog, etc. can also cause faults. In some extreme situations, such as a tornado, they may result in serious damage as breaking a transmission line conductor or causing the collapse of a transmission tower[1].

These factors and their impacts on faults are summarized in Figure 2-1.
2.2.2 Fault types

It is common to treat a healthy power system as a balanced symmetrical three-phase network. When a transmission line fault occurs, in most cases, the symmetry of the network will be broken, leading to unbalanced currents and voltages occurring in the network. The three phase fault is the only exception, which leads to a symmetrical fault, as all three phases are still equal at the same location when the fault happens [19].

In practice, all the faults can be divided into four categories[1]:

1. Single-phase to ground fault
2. Phase-to-phase fault
3. Double-phase to ground fault
4. Three-phase to ground fault

The single-phase to ground fault occurs the most in reality, followed by the phase-to-phase and the double-phase to ground fault. In contrast, the three-phase to ground fault is very rare.
Figure 2-2 to Figure 2-5 show some typical circuit diagrams for the different types of faults as mentioned above. It should be noted that these diagrams are plotted under the assumptions that the voltage of the network are wye-grounded connections and are provided through both ends of the faulted area. This holds true when overhead lines are used for the transmission system[19].

**Figure 2-2 Single phase to ground [19]**

**Figure 2-3 double phase to ground [19]**
Figure 2-4 Phase to Phase fault[19]

Figure 2-5 three phase to ground fault[19]
2.2.3 Influence of faults

Faults on a transmission line will affect the stability of the power system and the power quality that is delivered to users. For example, when there is a shorted fault, it will increase the level of fault current and this can cause serious damage to power system equipment and users cannot receive normal power. In the worst case, some of the power system equipment can be permanently destroyed and the whole power supply for users can be lost. It should also be noted that the faults are not avoidable, but if appropriate protection is used, the damage to the power system can be minimised[1].

2.3 Fundamentals of Protection

It was briefly introduced in the last chapter as to what the main power system protection means are and how it can be improved. More details regarding this will be explained here with particular emphasis on the TBP scheme.

A power system is designed to generate and deliver electrical power to consumers. A transmission line should be designed to deliver the energy both reliably and economically. However, faults on the transmission line can result in severe disruption of power delivery and the damage to devices. Therefore, faults on the power system transmission line must be detected and cleared as fast as possible to maintain system stability and minimise damage to devices. To minimise the adverse effects of faults, power system protection schemes are designed to achieve this goal[1].

The main function of the transmission line protection is to de-energise the faulted part as soon as possible to maintain the stability of a power system and minimise the damage of equipment during a fault. EHV transmission lines are implemented so as to transmit a large bulk of power. The faults on these transmission lines can disturb the delivery of power and then cause large economic loss and may cause large areas to blackout. Thus protection schemes on EHV transmission lines are of critical importance and are required to respond quickly and accurately[1].
2.3.1 Qualities required of protection

A few terms [20] are often used to describe the effectiveness of protection and they are listed below:

- Selectivity - the protection should only detect and remove faults in the protected zone.
- Stability - the protection should not operate for faults outside the protected zone.
- Speed of operation - It should be noted that the longer the fault current continues to flow, the greater damage it will happen. The ideal fault clearance time in EHV system should be as short as possible.
- Reliability - the protection should not operate in non-fault cases. This is to avoid circuit outages caused by the mal-operation of the protection itself.

2.3.2 Traditional Protection Principles

- Overcurrent protection

Overcurrent is one of the simplest amongst all of the protection schemes. It is actually based on the operating principle for the domestic fuse. The abnormal high current is often caused by the short circuit fault, particularly when the resistance of the fault is very low. In this respect, the actual cause of such a fault should be carefully considered within the protected zone. The protection schemes based on the overcurrent principle are usually calibrated on the graded time and current, or both, to ensure that the relay closest to the fault location reacts first. If it fails to do so, then the back-up relay should work, and so on, ideally along the direction outwards from where the fault happens. As the principle and the implementation is simple, it is widely used in a distribution network [20].

- Differential protection

The relay monitors the difference between the current that enters a protected zone and that leaves the zone. When there is no fault or the faults happening outside the protected zone, the relay detects no difference between the two currents. When the fault occurs in the protected region, there will be a transient overcurrent that can be
detected by the relay. Also by measuring the different currents at the zone boundaries
due to different impedances depending on where the fault is located, the fault
location can be determined. The down side of this method is that it requires
transducers at both ends of the protection zone as well as a reliable communication
link (which can be expensive and add complexity to the power system topology).
Therefore, this kind of scheme is mostly used for single localised equipment, such as
a busbar, generator or a transformer [21].

- Distance protection

This is traditionally the most popular non-unit protection scheme that is applied to
EHV transmission lines. Its basic principle is based on the measurement of
impedance on the protected zone, as the value of the impedance detected by the relay
is approximately proportional to the distance between the fault location and the relay
location[22].

Distance protection has several advantages, first of which is the fast operating speed,
which is the main consideration when engineers are choosing protection schemes for
an EHV transmission line.

From the voltage and current information detected by transducers, the relay can also
determine whether the fault is within the protected line. This is briefly explained here
- as shown in the following equation, the impedance equals voltage divided by
current gained by

$$Z = \frac{V}{I}$$  \hspace{1cm} \text{eqn 2-1}

When this value is less than the prescribed impedance, then a decision that a fault is
on the protected line can be made by the relay[19].

The disadvantage of this scheme can be summarized below[22]:

- It cannot protect the full 100% of the line.
- It is very sensitive to power frequency related phenomenon such as power swings

2.3.3 Transients Based Protection

The aforementioned traditional protection schemes have one common principle: they are based on the sampling of the quantities at the power frequency. If a fault on a transmission line occurs, there will be a short time period where the power frequency voltages and currents right across the whole system experiences pollution caused primarily by high frequency signals. This is due to the step change (caused by the fault) before they reach a steady state condition [15].

Since the traditional relays only make use of the power frequency signals, all the other frequencies must be filtered to minimise relay mal-operation. A band-pass filter is usually used within the relay design to deal with this to ensure the fault detection accuracy. Even so, there are still many limitations of such schemes. For example, the requisite signals must be measured for at least one cycle at the power frequency of 50Hz and this is too slow for protection purposes. Also, to remove the high frequency signals will add cost and complexity to the relay design. Moreover, the relays might trip due to an unfaulty situation, such as electro-mechanical oscillations due to the generators, which also occur at the power frequency. Other phenomenon like power swings, etc. can also result into a false trip alarm[19].

A fault on a transmission line produces wideband transients, the frequency of which is from DC component up to several hundred kHz. It is an electromagnetic phenomenon whose behaviour depends on the electrical parameters of transmission line components. These components consist of series shunt distributed R, L and C which are distributed along the entire length of a transmission line. As a consequence, the fault generated travelling waves propagate from the fault point with multiple reflections and refractions at the transmission line ends and any discontinuities. The observed fault transients are the composition of these travelling waves, which are dictated by the reflection and transmitted moduli at the busbars and the fault inception point. Due to the sudden voltage change caused by the fault, the magnitudes of transients on faulted phase(s) are larger than those of sound phases.
Based on this fact, faulted phase(s) selection can be developed under different system and fault conditions [19].

With the rapid development in computer technology, it is possible to develop protection methods that make use of the high frequency signals occurring in the transient time period for fault detection and analysis. This type of a protection scheme is commonly called Transient Based Protection (TBP) scheme[15].

There are essentially three major advantages that TBP has and should therefore be used instead of the traditional methods [15]:

- Fast response time, which is of critical importance for power system protection
- Not sensitive to normal system phenomenon occurring at power frequencies (e.g. power swing)
- The whole line can be protected

2.4 Simulation and Analysing Tools

There are a number of tools and techniques for simulating power transmission lines and analysing the fault transients; some of the more relevant ones are briefly introduced in this section.

2.4.1 Power System Simulation - EMTP and MATLAB Simulink

The TBP schemes require very precise modelling in the time domain for the power system under fault and normal conditions. The accurate modelling is a prerequisite to ensure a robust fault decision by the relay and its capability of distinguishing fault and non-fault conditions. EMTP (the Electromagnetic transients program) is one such powerful tool that can simulate the power system transients accurately and provide these high frequency signals for further post-processing and analysis [23].

The program was initially used for simulating the line switching of the power transmission line, but later became increasingly complicated due to various applications when the software was developed. Around the 1980s, users needed to have very specialized knowledge to operate this software, which hindered further
development and application of the tool [24]. Fortunately, this was noted by some experts in this area and they came up with an Alternative Transients Program (ATP) which is easier to use and more user friendly. The ATP version with a graphical window interface for the pre-processing - ATP-draw is now widely used today due to the development of Windows operating system [25].

It should be further noted that MATLAB Simulink [26] toolbox is commonly used to model, simulate, and analyse dynamic systems in various scientific and industrial areas, such as power systems etc. In this work, the toolbox is found to be an appropriate substitute for EMTP to simulate the power systems with/without wind turbine farms, since the current signals simulated from it is comparable to that obtained from the latter. This allows the protection scheme herein to be improved, tested and realized using only one piece of software, as the feature extraction and decision making steps of the power protection scheme are done using toolboxes in MATLAB.

It should be mentioned that the initial research based on the 400kV UK transmission system was using the EMTP and MATLAB software. However, due to the aforementioned reasons, the 500kV China was modelled and designed totally using MATLAB.

2.4.2 Feature Extraction – The Wavelet Transform

As mentioned before, on one hand, there is plenty of information contained in the transient signals due to the fault inception, and this can then be employed to develop power system protection schemes. On the other hand, the signals contain too much information to realize fast processing and response. As a result, it is of critical importance to extract the most useful information or features out from the transients for decision making. There are a few methods [9, 27-31] developed by researchers and engineers to solve this problem - the wavelet transform (WT) is chosen for this study due to its capability of time-frequency localization and handling irregular signals, which means that it can make use of information in both time and frequency domain even when the signals are not periodic. This feature allows the protection scheme to be more accurate and adaptive and to be used on-line. In contrast, the
traditional Fourier Transform (FT) can only make use of frequency information from the periodic signal and cannot run in real time[32].

The basic principle of the WT is very similar with the FT, but unlike the Fourier analysis that breaks up a series of signals into sine wave functions at different frequencies, the wavelet method decomposes the signal into scaled and shifted versions of the so-called mother wavelet [32].

A mother wavelet is a basic waveform of limited time duration and should have an average amplitude of zero by definition. To explain this more clearly, such a wavelet is plotted in Figure 2-6. It can be seen that the wavelet can be more irregular than the normal sine wave[33].

![A typical mother wavelet](image)

**Figure 2-6 A typical mother wavelet [34]**

In the protection scheme developed herein, the WT is applied to decompose the current signals into a series of detailed wavelet components, each of which is a time-domain signal that covers a specific frequency band. Also it has the ability of very effectively realizing non-stationary signals and signals with sharp changes (characteristics of faulted transients) comprising of low- and high- frequency components (such as those commonly encountered in power systems networks) through the use of a variable window length of a wavelet.

More details on this will be given in chapter 5. The Wavelet Toolbox in MATLAB Software is chosen to realize the WT of the fault current signals.
2.4.3 Pattern Recognition – The Neural Network

The working principle of the traditional protection scheme is to compare the calculated electrical values based on measurements to the prescribed safety thresholds. The safety settings must cover the fault conditions in the worst case scenarios. This requires very sophisticated system analysis and verification through field trials to ensure the threshold values are appropriate. Also its flexibility is restricted as only one criterion can be considered at a time[4].

The issues mentioned above cannot be handled by traditional techniques, but by new methods like artificial intelligence techniques. One appropriate candidate is the artificial neural network (ANN) technique which has been applied in electrical engineering for some years [35, 36].

ANN is motivated by research into the human brain. It has been demonstrated that ANN can learn complex non-linear relationships and modular structures when it is properly designed and trained. ANN can also solve non-algorithmic type problems, for example, it can handle problems for which algorithms cannot be established but significant data is available [18].

The characteristics of non-linear and large-scale generally make power systems difficult to deal with. For a non-linear and larger-scale system, there is no suitable analytical technique which is capable of solving complex problems. However, ANN offers an attractive way to deal with it due to its ability of mapping nonlinear patterns. Some advantages of ANNs are listed below [37]:

a) ANNs are adaptive: they learn from the input data. They can infer a proper solution from the input data and can capture quite subtle relationships of input data. As ANN does not depend on the programmer’s prior knowledge of rules, it is different from standard software techniques. ANNs do not require finding the exact relationships of input data, therefore it can reduce the development time when such relationships are difficult to find.

b) ANNs can generalize: they have fault tolerance and are able to handle imperfect data as well as incomplete data. Also, they are able to process data
which are similar to the data used for training. This feature is very important in real applications as data is noisy in the real world.

c) ANN networks are nonlinear: they are able to map complex relationships among the input variables. This is particularly useful for handling non-linear systems, e.g. power systems.

d) ANNs are highly parallel: due to their topology, the calculations can be done in parallel.

Many successful applications of ANNs in transmission line protection research have been described in [8, 16, 38-40]. Success also has been achieved in the development of the protection scheme in this work.

Neural Network Toolbox™ [41] in MATLAB is widely used to model complex and nonlinear systems that cannot be easily described by equations. The toolbox contains all the necessary elements for solving problems, i.e., neural networks can be designed, trained, and tested within the frame of it. In general, the tool box can deal with problems like clustering, pattern recognition, time-series prediction, data fitting, and dynamic system modelling and control[26].

2.5 Summary

This chapter introduces the fundamental principles that are related to the power protection scheme proposed in this thesis. The reason for faults and fault types as well as their influence are briefly reviewed. The fundamentals for the protection schemes are discussed and analysed, followed by an overview of the relevant techniques.

It has been outlined herein how a power protection scheme may be realized based on techniques such as WT and ANN. The scheme as well as the techniques will be introduced in greater detail in the following chapters. More details will be given in the next chapter, to explain why a new TBP scheme is needed and how it will be uniquely different from the other TBP schemes already developed.
Chapter 3  Literature Review on Transients Based Protection

3.1 Introduction

This chapter gives an overview of literatures and research projects on the topic of transients based protection (TBP) schemes. Firstly, a general review is given including why TBP is proposed and how TBP is evolved. This is followed by a description of how the wavelet transform has been applied to these types of schemes and then a review on non-unit TBP schemes. As the phase selection scheme is adopted in this work to enhance the performance, a brief introduction of TBP based phase selection is also given. At the end, the advantages of the TBP proposed in this work over the other TBP schemes are analysed and summarized.

3.2 Transients Based Protection (TBP)

A sudden change of system voltage caused by a fault generates voltage and current transients on an EHV transmission line. The frequency of fault transients is from DC frequency components to several hundred kHz components. As the fault transients contain a lot of fault information (fault type, locations, etc.), which contain both high and fundamental power frequency, they have been widely used in developing transient based protection schemes for transmission lines for years due to the advent of microprocessor-based techniques.

Johns [5] developed a protection scheme for high voltage transmission systems which uses high frequency fault transients derived from a tuned circuit connected to a CVT. The technique is based on conventional directional detectors which perform the HF stack-tuner switching. However, they are limited by conventional power-frequency signal measuring equipment. In 1994, Johns [16] demonstrated a new protection scheme based on non-unit measurements using HF fault signals which overcomes the above-mentioned limitations through specially designed transducers and algorithms that can overcome the bandwidth limitation of conventional transducers [16, 17]. The aforementioned research work constitutes a major step in utilizing fault generated high frequency components to develop new protection principles which signifies a new generation of protection, the ‘Transients Based Protection’ (TBP) [15].
3.3 Unit TBP using the wavelet transform (WT)

Fault transients from a transmission line have both low frequency long duration components and high frequency short duration components. WTTs have the ability of analysing these fault transients signals in both time and frequency domain quickly and efficiently. Therefore, it can be used as a feature extraction tool to extract useful characteristics of fault signals and then to develop a protection scheme based on fault transients.

A high speed EHV transmission line protection based on discrete wavelet transform (DWT) is described in [42]. In this work, the spectral energy of the WT coefficients from the decomposition of the current signals are calculated and used to detect faults. In [43], a high voltage transmission line unit protection based on the WT results of voltage transient signals at both ends of the transmission line is demonstrated. WT is used to decompose fault voltage into different frequency bands. Then the protection setting is based on the calculation of transient voltage content ratio. The results show that the protection scheme can protect the whole of the transmission line and the performance of the protection scheme is robust under different fault locations, fault types and system status.

In [44], Duan et al. demonstrated an ultra-high-speed directional protection scheme for EHV transmission lines based on WT. The high-frequency components of voltage and current signals are extracted by the WT and then its wavelet transform spectral energy (WTSE) is used to represent the transient energy of high frequency transients. Then by comparing the WTSE values of relays at both ends of a transmission line, the relay can identify the fault direction.

These above methods have good performance in fault detection. However, they are unit protection and the relays rely on the reliability of the communication links between both ends of the transmission line. Furthermore, their settings are quite complex.
3.4 Non-unit TBP scheme

It is apparent that non-unit protection schemes which can protect the whole transmission line (similar to unit protection) have obvious advantages. This is because traditional non-unit protections such as distance protection cannot protect the whole transmission line and settings are complicated. In contrast, traditional unit protection such as current differential can protect the whole line but communication links are required which can increase the cost of relay and the reliability of the scheme relies on the reliability of communication links[15].

Due to the significant fault information contained in the fault transients, the TBP protection scheme provides an alternative to develop a new non-unit protection scheme.

The first attempt was made in [16, 17] where the scheme was based on fault generated voltage transient signals. In this scheme, the specially designed high frequency voltage transducers are needed. In [45], Bo, Z.Q developed a non-unit protection scheme utilizing the fault generated current transients which have distinct advantages over the schemes based on voltage signals. Reasons are: firstly, current transformers (CT) have much wider bandwidth than CVTs and this overcomes the bandwidth limitation problem of the latter. Moreover, CTs are easy to interface and using current transients makes the scheme viable particularly when CVTs are not available. (This can be the case in some transmission systems). However, the limitation of this scheme is that line traps are required at both ends of the transmission line and this increases the costs.

Bo et al. in [13] demonstrates a non-unit protection scheme using fault current transients from the CT at only one end of the protected transmission line. This technique does not require any line traps and relies on the discrimination of high frequency components inside and outside the transmission line due to the attenuation of high frequency transients by a busbar capacitor to discriminate between internal and external faults. However, it has some drawbacks: only high frequency signals are used which means high frequency signals from disturbances such as switching, etc. may affect the performance of protection and also specially designed filters are
needed for selecting the desired bands of high frequency components. Moreover, this scheme has problems to distinguish the internal and external fault close to remote busbar.

Nan Zhang [4] presents a non-unit protection scheme based on both high and low frequency fault transients which can eliminate the impact of non-fault high frequency signals. Wavelet and self-organised neural network technique are used in this technique and both voltage and current fault transients are employed. However, the use of voltage signals makes the technique less practical due to the bandwidth limitation of CVT and different feature extraction methods are required for phase selection and fault detection functions which make the technique complicated and limits the speed of protection.

In [46], a non-unit transmission line protection is introduced which is based on current signals using the WT. It is based on the current signal of one phase of the three phase systems. The results show this method has good performance in detecting fault and fault type selection. However, as it is based on one phase current signal only, it does not have a phase selection function. To perform a single-pole tripping, phase selection is required, which is the limitation of this method. Another drawback is that the very high sampling rate (500 kHz) used by this method will require a very powerful microprocessor.

### 3.5 Transients Based Phase Selection Schemes

In this thesis, the phase selection scheme is developed to improve the performance of the protection scheme. Faulted phase selection plays a critical role in some types of protection techniques employed on a transmission line. The main purpose of faulted-phase-selection in this work is to correctly identify the type of fault, which is a prerequisite to the development of the WT and AI based protection technique described herein.

Traditional phase selection methods are based on components at the power frequency which contain limited fault information. It is difficult to maintain high accuracy under different system and fault conditions using these methods. Fault generated frequency components in these schemes are usually removed by filters. As a matter
of fact, such wide band frequency components have much useful fault information that can be used to identify fault types under different system and fault conditions[8].

In [47], the authors use superimposed transients of voltages and currents initiated by a fault to design a phase selection scheme. It is faster and more robust than traditional phase selection schemes which are based on power frequency components, as it uses a large frequency band which contains extensive information about the fault. Importantly, the effect of normal steady state components is very much mitigated.

In [8], a faulted selector based on high frequency voltage components generated by a fault is demonstrated. This method is also based on ANN technique which has a good pattern recognition ability for classifying fault types.

In [9] and [10], a phase selector based on the WT that is adopted to extract the characteristics of transients is proposed. In [10], four-level decomposition is used to analyse the three-phase voltages; these components are compared together and used for the phase selector. The use of WT as a feature extraction naturally emphasizes the difference between voltage waveforms of healthy and faulty phases as generated by the EMTP.

In [11] and [12], phase selection based on voltage and current signals using the WT and ANN is demonstrated. The WT is used as an extractor of distinctive features in the current and voltage signals. This extracted information is fed into an ANN for classifying fault types.

The major limitation of the aforementioned techniques based on high frequency signals is the limited bandwidth associated with the CVTs which severely attenuate the frequency components above about 1 kHz. As a direct consequence, the accuracy and robustness of the technique is compromised.
3.6 Summary

In summary, the current TBP protection schemes have the following drawbacks:

1) They use voltage signals measured by CVTs which have poor frequency responses that adversely affect the performance of TBP.

2) A special designed stacked tuner is required to capture high frequency components which increases the cost and makes the schemes complicated.

3) They only use high frequency components and the lower frequency components are discarded.

4) They require a high sampling rate, which is normally around 100 kHz and this requires very powerful and expensive microprocessors.

5) The penetration of the renewable energy is not considered.

In this thesis, a novel TBP protection scheme based on fault current signal using WT and ANN techniques are developed to overcome with aforementioned problems and provide an EHV transmission protection which is fast and reliable. As this is an UK-China joint research program, the scheme is first developed based on a typical UK 400 kV EHV transmission system and then applied to a typical Chinese 500kV EHV transmission system without and with wind farm penetrations.

There are several advantages of this technique:

   a) It only uses current signals from one end of the transmission line. In reality, the frequency bandwidth of CTs (about 70 kHz) is much wider than that of the CVTs.

   b) The phase selection scheme which can classify fault types is developed to improve the performance of the protection scheme.

   c) Both high and low frequency signals are used to help improve the performance of the scheme. Normally, TBP only uses high frequency transients. However, low frequencies also contain very useful information for
fault detection. Also using both high and low frequency components can help eliminate the impact of non-fault high frequency signals [4].

d) A relatively low sampling rate 16 kHz is used, compared to high sampling rates (100 kHz or higher) employed in many other TBP techniques. Therefore, the scheme proposed in this thesis clearly has lower hardware requirements (i.e. a more cost effective microprocessor).

e) The effect of wind power is also considered in the development and the flexibility of the technique is potentially increased.
Chapter 4  System Simulation and Signal Analysis Method for Fault Generated Transients

4.1  Fault transients detection based on EMTP

This section gives an introduction to the modelling of the EHV transmission system in EMTP. A typical UK 400kV system is chosen for developing the protection scheme as a starting point. The EMTP software is a well-proven programme for simulating the electromagnetic in power systems as discussed in [23]. The EMTP model will serve as the basis for developing the protection scheme that is based on the fault current transients. As discussed in the former chapter, the protection scheme developed herein is based only on fault current signals.

In this section, EMTP is introduced in the first part, followed by the description for the specific model used for this study. Simulations of the different fault types under different conditions (e.g. fault inception angles, fault locations, etc.) are conducted and the resultant fault current signals are typified and discussed.

4.1.1  Simulation Tool - EMTP

EMTP-ATP has been extensively used and very well proven in terms of its ability to model the power system in both the academic and the engineering community, especially for simulating the electromagnetic transients. This is vital for the accuracy of the protection scheme as an accurate simulation of the power system can ensure that distinct differences between fault and non-fault conditions can be well brought out.

As a consequence, simulating a typical EHV power transmission system in EMTP-ATP was chosen as the first step for this work to lay the foundation for developing the new power system protection scheme.

4.1.2  Electrical Power System Model

The transmission system model is set-up by defining the source and power transmission line in EMTP, respectively. The details on how and why they were set-up are introduced below.
Source Representation

Since the period of the electromagnetic transients studied here are very short (typically from 100 to 230ms for EHV transmission lines), it is justifiable to represent the source by a voltage source behind a transient reactance[48].

For EHV transmission systems, the equivalent transient reactance is approximately 50-100 times greater than the resistance, hence the resistance can be neglected in the calculations [1].

Thus it can be said that:

\[ P \approx \frac{V^2}{X} \]  
\[ \text{eqn 4-1} \]

Where \( P \) is the short circuit level of the power of the generator in VA, \( V \) is the line to line voltage in V and \( X \) represents the reactance.

Hence:

\[ X \approx \frac{V^2}{P} \]  
\[ \text{eqn 4-2} \]

And the resistance (if necessary) is

\[ R \approx \frac{X}{100} \]  
\[ \text{eqn 4-3} \]

Thus for the power sources at the sending and receiving ends of the EMTP model, a capacity of 5 GVA, a resistance of 0.32Ω and a reactance of 32 Ω are used, as shown in Table 4-1 and this is based on a 400kV transmission system.
Table 4-1 Parameters of Source Side Networks

<table>
<thead>
<tr>
<th>Capacity</th>
<th>Resistance/ohms</th>
<th>Reactance/ohms</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 GVA</td>
<td>0.32</td>
<td>32</td>
</tr>
</tbody>
</table>

• Transmission line

It is assumed that the electrical parameters of the transmission line studied here are distributive in nature for the fault analysis of the EHV power transmission system. Therefore, the J-Marti line model [49], that is well proven for transient studies, is used in the simulation. For the J-Marti line model developed in ATP-draw, users can set the actual geographical location of the conductors and their properties, and then calculate the related parameters of the line modelling. Table 4-2 gives the details of such parameters [50].

J-Marti model refers to an improved line modelling method where the weighting function of a receiving network can cancel out the forward weighting function - this feature can significantly reduce the complexity of a convolution integral, and hence the amount of the necessary computation time can be significantly reduced[49].

Table 4-2 Parameters of Transmission Line [50]

<table>
<thead>
<tr>
<th>Ph.no.</th>
<th>React</th>
<th>Rout</th>
<th>Resis</th>
<th>Horiz</th>
<th>Vtower</th>
<th>Vmid</th>
<th>Separ</th>
<th>Alpha</th>
<th>NB</th>
</tr>
</thead>
<tbody>
<tr>
<td>#</td>
<td>[ohm/km AC]</td>
<td>[cm]</td>
<td>[ohm/km AC]</td>
<td>[m]</td>
<td>[m]</td>
<td>[m]</td>
<td>[cm]</td>
<td>[deg]</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>1.1573</td>
<td>0.2953</td>
<td>0.016936</td>
<td>6.95</td>
<td>31.4</td>
<td>25.4</td>
<td>30.5</td>
<td>45</td>
<td>4</td>
</tr>
<tr>
<td>2</td>
<td>1.1573</td>
<td>0.2953</td>
<td>0.016936</td>
<td>8.3</td>
<td>12.2</td>
<td>11</td>
<td>30.5</td>
<td>45</td>
<td>4</td>
</tr>
<tr>
<td>3</td>
<td>1.1573</td>
<td>0.2953</td>
<td>0.016936</td>
<td>10.2</td>
<td>21</td>
<td>17</td>
<td>30.5</td>
<td>45</td>
<td>4</td>
</tr>
<tr>
<td>4</td>
<td>1.1573</td>
<td>0.3656</td>
<td>0.016936</td>
<td>0</td>
<td>41.5</td>
<td>35.1</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

4.1.2.1 EHV power transmission system model

The simulation of the power system was then carried out in EMTP-ATP based on the parameters as shown in Table 4-1 and Table 4-2.
Figure 4-1 shows how the model of the power system as studied in this project when it is set up in the EMTP. The overhead transmission line used herein is based on a single circuit of a typical 400 kV transmission line. It consists of two sources connected by a three phase transmission line of 128 km. The capacity of each source is 5 GVA. The fault resistance to ground is taken to be 2 Ω and the power system frequency is taken to be 50 Hz. An X/R (reactance/resistance) ratio of 100 was used for each source terminating a busbar.

The simulation is based on a sampling frequency of 16 kHz and the current data is obtained from the simulation output file. There are two reasons for the 16 kHz sampling rate. Firstly, if the sampling rate is higher, more powerful microprocessors are needed which will result in more costs in real systems. Secondly, if the sampling rate is lower, the high frequency information contained in transients cannot be properly captured.

![The EMTP model for the UK 400kV EHV power transmission system](image)

**Figure 4-1 The EMTP model for the UK 400kV EHV power transmission system**

To simulate the faults, one can set up the time for when the fault can occur, which phase(s) has a fault and where the fault occurs in the EMTP model. Thus, it is possible to simulate different fault scenarios, e.g. different fault phases, different fault locations and different fault inception angles. After the completion of each simulation study, the fault current signals can be extracted from the output file.

### 4.1.3 Simulation results

In order to understand the fault current signal behaviour especially how it varies under different fault conditions, the simulation results of the fault current are shown and discussed extensively in this section.

To be more specific, the current waveforms have been generated based on the power system studied under different situations such as various fault locations, various fault
inception angles, etc. In a real power system, any type of fault can happen as it is unpredictable. Therefore, more situations are considered in the simulations, more robust the protection scheme is.

The current waveforms for single-phase to ground, phase-to-phase, double-phase to ground and three-phase to ground faults have been simulated at different fault positions and different fault inception angles, the latter only for phase to ground and phase to phase faults. The simulation model and the fault current waveforms for each specific fault are demonstrated here. The results are classified into three categories (different fault types, different fault inception angles and different fault locations) for better comparison and are shown respectively in the following sections.

**4.1.3.1 Effect of Different Fault Types**

As described above, the faults occurring on a transmission system are of different types, depending on which phase the fault occurs and if the ground is involved or not.

**4.1.3.1.1 Single-Phase to Ground Fault**

As there are three phases in studies associated with a power system, there is phase A to ground (AG) fault, phase B to ground (BG) fault and phase C to ground (CG) fault that are included in the single-phase to ground fault. This is supposed to be the most common fault among the entire fault situations - it constitutes approximately 70%-80% of total faults[1, 2].
It is shown in Figure 4-2 that how the current signal varies with time from a power system simulation, where there is an AG fault occurring at 20ms. It shows clearly that, after the fault occurs, the magnitude of the current of the faulted phase A is much higher than that of healthy phases B and C. This is due to the sudden decrease of the resistance between the phase A and the ground. For the fault presented in this figure, it happens at 32km away from the sending end and the fault inception angle is 90°, i.e. when the voltage is at its maximum value for this phase.

However, the transients that are proposed to be used in the development of the new protection scheme herein cannot be clearly seen in this plot. Analysis tools will be required to make the features visible so that further analysis and judgements on them can be made.

Although not shown here, very similar trends are also observed in the simulation of the BG and CG faults. (Also see appendix A)

4.1.3.1.2 Phase-to-phase fault

The second type of the classical fault is the phase-to-phase fault, where one can have A-phase to B-phase (AB) fault, B-phase to C-phase (BC) fault and C-phase to A-
phase (CA) fault; this effectively means there is a short circuit between the two phases.

Figure 4-3 Fault current waveforms for AB fault, 32km, 90°

Figure 4-3 typifies the time variation of the current signal for the AB phase fault occurring at 18.5ms. It shows clearly that, after the fault occurs, the magnitude of the faulted phase A and faulted phase B currents are much higher than that of the healthy phase C, as expected. Also, the signal for phase A and phase B is symmetric against the time axis, i.e., at one time point, they have exactly the same magnitude but opposite sign. This is again due to the sudden decrease of the resistance between phase A and B, and they are in the same loop due to the fault. The fault also happens at 32km away from the sending end and the fault inception angle is 90° with respect to the line voltage AB. Very similar trends are also observed in the simulation of the other two types of faults and are thus not shown here. (Also see appendix A)

Again, no fault transients are visibly apparent in these waveforms and this warrants further analysis to separate out the relatively small-magnitude transients.
4.1.3.1.3 Double-phase to ground fault

Double phase-ground faults are relatively less common compared to the aforementioned single-phase to ground and phase to phase faults. However, they need to be considered when developing a protection scheme. Such faults are: A-B-phase to ground (ABG), C-A-phase to ground (CAG), B-C-phase to ground (BCG). The behaviour of the current signals caused by these types of faults is, as expected, slightly more complex than the two faults introduced before. An ABG fault is simulated again at 20ms and the current signal is shown in Figure 4-4. The distance of the fault to the sending end remains unchanged. No fault inception angle can be defined in this case. The involved faulted phases show significant different currents compared to the healthy phase after the fault time point, and due to the involvement of the ground, they are also different from the pure AB fault. There is also an offset in the signals. To include this in the protection scheme, the data need to be dealt with is increased in terms of volume and complexity and the requisite analysis will be dealt with later.

![Fault current waveform of ABG fault, 32km](image)

**Figure 4-4 Fault current waveform of ABG fault, 32km**
4.1.3.1.4 Three-phase to ground fault

The worst case scenario occurs when all the three phases are connected to ground i.e. the A-B-C-phase to ground (ABCG) fault. As typified in Figure 4-5, all three phases have sudden significant changes in the current signals. Such faults are very rare, but it should nevertheless be considered in any protection scheme. The distance of the fault to the source is 32km. No fault inception angle can be defined in this case.

![Figure 4-5](image)

**Figure 4-5 Fault current waveform for ABCG fault, 32km**

4.1.3.2 Effect of Different Fault Inception Angles

It should be made noted that in practice a fault can occur at any phase angle of the voltage waves and it is thus vitally important to check if the power system protection scheme can handle all the various fault inception angles. Herein, two extreme cases are examined and presented, i.e. a fault occurring at voltage zero and voltage maximum respectively (see also Figure 4-6). That being said, only the single-phase to ground fault and phase-to-phase fault has different fault inception angles. For the former case, it is straightforward to define this fault inception angle; in contrast, that for the latter case it needs to be calculated in the way explained below. And for the
double-phase to ground and the three-phase to ground faults, it is not possible to clearly define the fault inception angles.

![Voltage Wave](image)

**Figure 4-6 Typical voltage wave for each phase**

For calculating the phase angle for a phase-to-phase fault, the phasor diagrams are required to calculate the voltages, as shown in Figure 4-7. The three sub-figures correspond to three different fault types - AB, BC and CA. Based on the analysis as shown in the figure, the fault inception angle for the phase-to-phase fault can be well defined and the corresponding results can be generated and analysed.

Figure 4-2 and Figure 4-8 show the current signals for the AG fault at fault inception angles of 90° and 0° respectively. The two faults are both located at the 32km away from the sending end. By comparing those two figures, a few observations can be made here:

1.) The shape of the current signal due to the faults is very similar

2.) The current amplitude raised by the faults is no longer a time-axis-based regular sine wave for the 0° inception angle compared to that for the 90° inception angle. A DC phase shift is seen for the 0° case.

3.) The healthy phases are barely influenced by different fault inception angles.

Although not shown here, the above observations are very similar for the BG and CG fault.
Figure 4-7 Phasor diagram for three types of faults (a) AB (b) BC (c) CA

Figure 4-8 Fault current waveform for AG fault, 32km, 0°
Figure 4-9 Fault current waveform for AB fault, 32km, 0°

Figure 4-3 and Figure 4-9 illustrate the current waveform for an AB fault at the fault inception angle at 90° and 0° respectively. Again the fault distance is 32km from the sending end. The similarities and differences in the two cases are summarized below.

1.) In both cases, the faulted phases A and B have current waveforms of opposite polarity. Their shapes are also very similar.

2.) In the case of the 0° inception angle, the current signal after the occurrence of the fault is no longer a time-axis-based regular sine wave compared to that for the 90° inception angle. A DC phase shift is seen for the former case.

3.) The healthy phase C is insensitive to the different fault inception angles.

Although not shown here, the waveforms for BC and CA phase to phase fault are similar to those for the above fault.
4.1.3.3 Effect of Different Fault Locations

A fault can occur at any position on a transmission line. As shown in Figure 4-10, the power transmission line has a total length of 128km. To examine how the distance to fault from an end can influence the current signal, distances of 8km, 56km, 88km, 120km from the sending end to the fault are simulated and presented. These correspond to Figure 4-11 to Figure 4-18 respectively. The fault types include AG fault, AB fault, ABG fault and ABCG fault; the former two cases have a fault inception angle of 90°.

In the cases considered, it can be seen that the current signals after the fault inception point all have somewhat similar behaviour with the exception of a variation in the amplitudes and also the frequency of distortion superimposed on the power frequency component.

In particular it should be noted that, as the fault location approaches the receiving end, the transients become more prominent and are of relatively lower frequency. This is expected as the wave propagation time between fault and the sending end increases in the latter case.

However, a comparison of the fault transients (fluctuations) amongst the cases from the figures shown here are not very discernable and hence better analysing tools are required so that the whole picture with regard to the fault transients can be better depicted.

As a brief summary, it is should be noted here that from all these current waveforms plots, it can be easily seen that thefaulted phase(s) has large changes at the fault point while the healthy phase(s) is also influenced but only small changes are seen.
Moreover, all the different fault types will result in different phase current waveform characteristics.

Due to the complexity of the information needed to be dealt with, it is not enough to design an accurate and fast protection scheme based directly on the signals discussed in this section. In the following section the fault transients associated with practical scenarios will be analysed using the WT technique and the results will be discussed in more details to help define the steps required with the development of a novel power protection scheme.

Figure 4-11 Current waveform of AG fault, 90°, left - 8km, right - 56km

Figure 4-12 Current waveform of AG fault, 90°, left - 88km, right - 120km
Figure 4-13 Current waveform of AB fault, 90°, left - 8km, right - 56km

Figure 4-14 Current waveform of AB fault, 90°, left - 88km, right - 120km

Figure 4-15 Current waveform of ABG fault, left - 8km, right - 56km
Figure 4-16 Current waveform of ABG fault, left - 88km, right - 120km

Figure 4-17 Current waveform of ABCG fault, left - 8km, right - 56km

Figure 4-18 Current waveform of ABCG fault, left - 88km, right - 120km
4.2 Fault signal analysis using wavelet transform

As shown above, the faults for different fault conditions are simulated and the raw data of fault current transients are acquired. In this section, the data will be processed using WT, the results of which are used to study the effect of different fault conditions on fault current transients, and the most significant information from the processed data will be determined and selected as part of the feature extraction stage; this being the prerequisite for the protection scheme.

Furthermore, the concept as well as the application of the wavelet and the WT will firstly be described in details. Then, how and why the waveform decomposition results from the WT should be made use of is explained. Lastly, the decomposition results under different fault conditions are discussed.

4.2.1 Wavelet and Wavelet Transform

Sine waves are the basis of the FT and can extend from minus to plus infinity in the time domain. They are smooth, predictable and periodic. In contrast, a wavelet, although also is a waveform, has very different features listed below [9]:

1.) It has only limited duration.

2.) It has an average value of zero.

3.) It tends to be irregular and asymmetric.

It is shown in Figure 4-19 how a widely used wavelet (Db10) is compared to the sine wave. It can be seen that there are significant differences in their properties such as the shape, the periodicity, etc.

Sine waves are the elements for the decomposition in the FT analysis. The original signal is decomposed into shifted and scaled sine wave functions in FT. Similarly, the wavelets are the basic elements for the decomposition in the wavelet analysis. The given signal is decomposed into shifted and scaled (mother) wavelets. Due to the different features of the basic elements (wavelet for WT and sine wave for FT), the two methods are suitable for the decomposition of different types of signals.
For example, WT will be more suitable for analyzing the signals with sharp and sudden changes, which can be judged from the shape of the wavelets, while the Fourier transform is more suitable for regular and periodic signals. Also as a result of the local extent of the wavelets, the local features of any signals can be analyzed better using the WT.

In electrical engineering applications, it has also been identified that FTs are not suitable for decomposing the non-periodic signal transients[32]. In contrast, WT is more useful for the signals with sudden changes and non-periodic nature such as that associated with transmission line switching operations and faults. Also, it provides both the frequency and time information compared to FT, which can only provide frequency information. This is useful in analyzing non-stationary signals comprising both LF and HF components. As shown in the previous section, the current signals due to the faults comprise sudden changes and behave irregularly with time, and hence the WT will suit better in the case of the latter.

Furthermore, it has been shown that the signal processing technique based on the WT is an effective tool for power system transients’ analysis and feature extraction in recent research. It has also been applied in power systems as it can analyse signals in both time and frequency domains[32, 51]. The two main areas of application of WT are in power quality analysis [33, 52-54] and in power system protection [9, 55, 56].

4.2.1.1 Mother wavelet and Discrete Wavelet Transform

It should be noted that for applying any WT, a mother wavelet needs to be chosen. This is critical for the detection and localization of the fault transients at different
situations. The most basic mother wavelet is called “Haar” wavelet, which was proposed by Alfred Haar[57] in 1909. It can be described as:

\[
\psi(t) = \begin{cases} 
1, & 0 \leq t < 1/2 \\
-1, & 1/2 \leq t < 1 \\
0, & \text{otherwise}
\end{cases}
\]  

It can also be seen in Figure 4-20 what it looks like. Daubechies wavelets family is nowadays the most commonly used wavelets and it is shown in Figure 4-21 from Db2 to Db10[32]. It should be noted that Haar wavelet can be taken as a special wavelet in this family as Db1.

**Figure 4-20 Haar Wavelet**
These wavelets in Figure 4-21 are very commonly used in both the engineering and academic community and their capability has already been well proven, thus they are also chosen to be tested herein and the results will be discussed later, in order to identify and select the appropriate mother wavelet for this study.

It requires much effort to resolve every wavelet coefficient in all the scales, which is also usually unnecessary. The same accuracy can already be achieved using the discrete wavelet transform (DWT) that is much more time-efficient, providing appropriate scales and positions. This means that wavelets in the transformation are discretely sampled instead of continuously. In fact, the real-world data is sampled in a discrete form using computers and the signal process must be performed based on them, and hence the DWT is used herein[32].

Mallat [58] has developed a fast method to implement DWT by using filters in 1988, which has become a classical scheme and is known as a two sub-band coder for the signal processing community. This algorithm is very practical and the wavelet coefficients can be calculated very efficiently as the signal passes by.

### 4.2.1.2 Approximation and Details

It is also important to know the definition of so called “approximations and details” in wavelet analysis. Approximation (A) indicates the high-scale, low frequency part of the signal while Details (D) represents the part of low-scale and high frequency,
like shown in Figure 4-22. To be more specific, high scale is to be represented by more “stretched” wavelet. Due to the wider time window included in the “stretched” wavelet, the resolution of the signal by the wavelet is also correspondingly lower. In contrast, low scale corresponds to more “compressed” wavelet and its narrow time window allows a higher resolution of the signal[26].

![Wavelet Components](image)

**Figure 4-22 High scale and low scale components of the wavelets [26]**

Thus, there is a correspondence between wavelet scales and frequency as revealed by the wavelet analysis[26]:

- Low scale - Compressed wavelet - Rapidly changing details - High frequency
- High scale - Stretched wavelet - Slowly changing - coarse features - Low frequency

The WT can be described using a filter process done on the original signal, like that shown in Figure 4-23. “A” and “D” are respectively the result when the original signal is sent through the low-pass and high-pass wavelet filters. To gain a better understanding of this progress, a one-stage DWT of a sine signal with noise is illustrated in Figure 4-24. It can be seen that the “A”, i.e. high scale component, is very close to the sine signal, with less noise compared to the original signal, while the “D”, only contains high frequency noise. This decomposition can be made to another level[26].
In reality, one-level decomposition is normally not enough to achieve enough information for analysis, in which case the multi-level wavelet transformation is required. In the process, the further details will contain gradually lower resolution or lower frequency components. The mechanism is illustrated in Figure 4-25; basically the original signal is first decomposed into $A_1$ and $D_1$; then $A_1$ is decomposed into $A_2$ and $D_2$ etc. as described in Figure 4-25.

The structure is called the wavelet decomposition tree. The tool used in this study for wavelet analysis is MATLAB wavelet toolbox. It has exactly the same working mechanism as mentioned above.
The transients detail represents the signal information in the frequency domain and the frequency band of each detail coming out from the DWT is shown in Table 4-3. The sampling frequency of the current signal is 16 kHz and therefore the highest frequency of the signal that can be resolved is 8 KHz (i.e. in D₁) based on the sampling theorem [59]. Also, as the level of the details goes higher, the frequency band of the Details coming out from the DWT becomes lower. At certain level, it will reach the power signal frequency, where the normal sine wave signal can be seen. It is arbitrarily chosen here to use 5-level-decomposition for comparison and the lowest frequency of the information resolved by the details is 250 Hz, still 5 times of the power signal frequency.

<table>
<thead>
<tr>
<th>Details Number</th>
<th>Frequency range</th>
</tr>
</thead>
<tbody>
<tr>
<td>D₁</td>
<td>8KHZ - 4KHZ</td>
</tr>
<tr>
<td>D₂</td>
<td>4k Hz - 2k Hz</td>
</tr>
<tr>
<td>D₃</td>
<td>2k Hz - 1k Hz</td>
</tr>
<tr>
<td>D₄</td>
<td>1k Hz - 500Hz</td>
</tr>
<tr>
<td>D₅</td>
<td>500 Hz - 250Hz</td>
</tr>
</tbody>
</table>
It is now worthwhile to check how the wavelet can handle the electrical signals dealt with in this work using an example. The fault current signal from the AG fault (32km from the sending end, 90° inception angle) simulated in the EMTP is taken as the input for the MATLAB wavelet toolbox. The mother wavelet is arbitrarily chosen to be Db4.

As shown in Figure 4-26, the $D_1$ to $D_5$ are the high frequency components (Details) from the wavelet transform aforementioned. The fault transients contained in the current signal are clearly shown in $D_1$ to $D_5$. The features are very distinctive, especially near the region of the fault inception point. It is undoubtable that they can be taken as the features that identify the faults. The information is exactly what is needed to realize a TBP scheme. It demonstrates that the wavelet analysis is capable of capturing the most important details in the fault transients.

![Figure 4-26 Decomposition of the current signal using wavelet analysis](image)

**4.2.1.3 Decision in the Choice of the Mother Wavelet**

As mentioned earlier, there are many types of the wavelets that can be chosen for analysis. To help decide which is the most appropriate type of mother wavelet that
should be used in this work, the Db1 until Db10 wavelets are used to realize the decomposition of a fault current signal. The fault current signal from a typical fault situation (AG) is selected.

Figure 4-27 shows what the results are like for the 5-level decomposition using Db1 to Db10. It can be seen that, when Db1 is applied, the A (Approximation) and D (Details) coefficients are not smooth and there is no distinctive feature at the fault point, which is not sufficient for supporting the power protection scheme. As the Db wavelet gets more coefficients and more complicated, the decomposition result becomes smoother and also the distinctive feature becomes more visible. For example, when Db10 is applied, the fluctuation and the major changes of the coefficients for D1 to D5 are distributed mainly around the fault point. As a matter of fact, after Db4, the features of the details have already become discernable and also the approximation is smooth; this can thus be used in the selection process for the inputs to the neural network (as discussed later) and the more complex Db wavelets are not necessary. Hence, Db4 is chosen for the study here. It should be mentioned that the aforementioned phenomena is true for all the practical fault scenarios considered in the development of TBP.

1)5-level signal decomposition by Db1  2)5-level signal decomposition by Db2
3) 5-level signal decomposition by Db3
4) 5-level signal decomposition by Db4

5) 5-level signal decomposition by Db5
6) 5-level signal decomposition by Db6
7) 5-level signal decomposition by Db7
8) 5-level signal decomposition by Db8

9) 5-level signal decomposition by Db9
10) 5-level signal decomposition by Db10

Figure 4-27 Fault Current Signal Decomposition by Db1 to Db10
4.2.1.4 Calculation of Spectral Energy

It can be seen from Figure 4-27, that the wavelet coefficients D1 to D5 around the fault inception point fluctuate between positive and negative values. Although, they are quite distinctive features for fault identification, they are not discernable enough to be directly employed in the decision making process about a particular fault; hence the spectral energy is firstly extracted from these signals and it can be calculated using the following formula:

\[ E_j(k) = \sum_{n=20(k-1)+1}^{20k} cD_j(n)^2, k = 1,2,3,... \]  

Where E is the spectral energy, n is the coefficient number, k is the window’s number, j is the wavelet decomposition level and cD is the magnitude of the coefficient for the details from WT. Each spectral energy data contains the energy during a certain window length. Here the number of 20 coefficients is selected. The reason is that too many will influence the time resolution and too less will impact on the accuracy. More details concerning this will be shown in the following section.

Based on the coefficients generated from the MATLAB wavelet toolbox, the spectral energy can be easily calculated and utilized using eqn 4-5.

4.2.2 WT Results for Different Fault Conditions

It is studied herein in detail how the WT performs when it is applied to decompose the fault current signal under different fault conditions. The study is based on the current signals generated using the model introduced in the last section. Four levels are decomposed and the corresponding spectral energy magnitudes are calculated. The decomposition level of 4 is arbitrarily chosen for illustration purpose and as the power protection scheme is developed, more levels would be required as shown later.

4.2.2.1 Effect of Different Fault Types

Results from the different fault types are first shown and discussed.
Figure 4-28 illustrates a 4-level wavelet decomposition of an AG fault at 16km from the sending end when fault inception angle is 90°. As can be seen from the figure, the faulted phase (red line), i.e. phase A, has a much bigger fluctuation compared to the other two healthy phases (black-phase B, blue-phase C) after the occurrence of fault. This feature is very apparent for all four level details. As discussed earlier, even though there are some significant differences, the coefficients are switching between positive and negative values, which brings additional difficulty to the decision making process. Therefore, the energy for the four level details is respectively calculated instead, using eqn 4-5, with a windows length of 20, i.e. each spectral energy data contains the information from 20 wavelet coefficients. And the results are shown in Figure 4-29.

As can be seen, after the data is processed using the above approach, it becomes apparent that the current magnitudes of the energy of the faulted phase are much higher than these of the healthy phases after the fault inception point. To be more specific, at D1, the highest magnitude of the phase A is 6x10^5 while that of phase B and C is much smaller. Moreover, in all the figures which contain the processed high frequency information, the transients reach a peak value and decays to zero. In other words, a spike appears at the fault instance. This indicates that there is a sudden change of fault related transients in terms of amplitude at the fault inception point, which clearly becomes visible by the WT.

As demonstrated, there is thus a clear advantage of using spectral energy instead of the individual information from the decomposition using WT; the features that distinguish the faulted and healthy phase is more outstanding in the case of the former. The utilisation of the spectral energy of the WT coefficients is thus the criterion adopted in the decision making process herein.

Figure 4-30 corresponds to an AB fault, where all the other variables (fault position, fault inception angle, etc.) are kept the same compared to the last case. As can be seen in the figure, on fault inception, the two faulted phases (A and B) both have significantly higher spectral energy levels than the healthy phase C for all 4 details from the wavelet decomposition. Note that the magnitudes of the spectral energies for both the faulted phases are very close to each other in all 4 details. The highest
spectral energy magnitudes for D₁ to D₄ are 9.5x10⁵, 1.2x10⁶, 2.5x10⁴ and 2.8x10⁵ for the faulted phases. Figure 4-31 illustrates the results for the faulted phases for ABG fault. In D₁ to D₄, the energy between the two faulted phase, A and B, are still quite similar. They are both much higher than phase C. The differences can be of crucial importance in distinguishing different types of faults.

Figure 4-32 shows the ABCG fault, when all the three phases are connected to ground. In this case, it can be seen that all the three phases have a sudden jump in terms of the spectral energy due to the occurrence of the fault. Phase A has the highest energy, while phase C has the lowest energy level for all the 4 level details but the magnitudes are quite comparable.

With the help of the WT analysis technique, irrespective of the different types of faults considered herein, there is always a peak shape of spectral energy for the faulted phase on fault occurrence. This is a very important common feature that can be made use of to realize the phase selection, i.e., to help determine the faulted phase(s) in the protection scheme.

Figure 4-28 4-level WT decomposition of the fault current signals AG fault, 16km, 90°
Figure 4-29 Spectral Energy variation with time for the 4-level WT decomposition of the fault current signals AG fault, 16km, 90°

Figure 4-30 Spectral Energy variation with time for the 4-level WT decomposition of the fault current signals AB fault, 16km, 90°
Figure 4-31 Spectral Energy variation with time for the 4-level WT decomposition of the fault current signals ABG fault, 16km

Figure 4-32 Spectral Energy variation with time for the 4-level WT decomposition of the fault current signals ABCG fault, 16km
4.2.2.2 Effect of Different Fault inception angles

This part describes the results for different fault inception angles. AG faults at 16km are chosen for this illustration. Two extreme cases are investigated, i.e. the 0° and the 90° faults.

Figure 4-33 and Figure 4-29 typify the spectral energy of AG faults at 0° and 90° respectively. It is apparent that, for all the 4-level details, in both cases, the faulted phase A has a significant higher spectral energy compared to the two healthy phase B and C. However, the magnitude of the spectral energy in the two cases, for each detail, is very different. For example, when the fault occurs at 90°, the highest energy of D1 is $6 \times 10^5$, compared to 160 for the 0° case. For D4, the two values are also different i.e. $1.7 \times 10^5$ and 8000 for 90° and 0° faults respectively.

For the other types of the faults (e.g. AB fault etc.), though not shown here, the differences are similar for the different fault inception angles. Apparently, the significant differences between the spectral energy values for the two different fault inception angles will add to the uncertainty and complexity in the phase selection scheme.
4.2.2.3  Effect of Different Fault Location

In this section, studies are presented relating to the influence of the fault location on the decomposition information of the faulted signals. Faults are set at 20km, 64km and 120km respectively from the sending end, i.e., one location close to the sending end, one location in the middle of the line and one location close to the receiving end. These three faults locations are fairly representative for typical faults between the two ends. B-phase-ground fault type is selected for this study and the fault inception angle is 90°.

Figure 4-34 shows when the fault occurs 16km away from the sending end. The black dashed line represents the spectral energy for phase B; the red and the blue lines represent phases A and C respectively. For D₁ to D₄, their values are significantly higher than the healthy phases; moreover, the peak of the healthy phase appears later than that of the faulted phase B. The picture becomes clearer when the fault occurs at 64km, as shown in Figure 4-35. From D₁ to D₄, the spectral energy of the faulted phase B is much greater than that of the two other phases; this would
serve very well for any phase selection scheme. The phase selection scheme must be capable of handling all practical situations; therefore the other cases are also checked. For example, the fault occurs close to the receiving end (120km) is shown in Figure 4-36, in $D_1$ to $D_4$, the spectral energy for the faulted phase is again higher than that of the healthy phases.

The aforementioned results do demonstrate 4-level decomposition of the faulted signals using the WT technique and the utilization of the spectral energy, the most important features can be extracted and can in principle be used to realize the selection of the faulted phase(s). However, the detailed analysis for different fault scenarios demonstrates the difficulty of developing such a scheme for all fault scenarios, more so, due to the levels of the spectral energies in the WT components being somewhat similar in the case of faulted and healthy phases.

Figure 4-34 Spectral Energy variation with time for the 4-level WT decomposition of the fault current signals BG fault, 16km, 90°
Figure 4-35 Spectral Energy variation with time for the 4-level WT decomposition of the fault current signals BG fault, 64km, 90°

Figure 4-36 Spectral Energy variation with time for the 4-level WT decomposition of the fault current signals BG fault, 120km, 90°
In a summary for this section, the 4 level WT decomposition of the faulted current signals from several typical fault situations (i.e. different fault types, different fault locations, different fault inception angles) are shown and discussed above. They all show different extent of impact on the WT and spectral energy results. It can be seen that, while the most important features of the signals are extracted by WT analysis and spectral energy calculation, i.e. the spectral energy peak for faulted phase etc., there are still difficulties to effect any simple phase selection scheme due to the existence of similar energy values between the faulted phase and the healthy phases for some fault scenarios. A simple threshold approach to identify the faulted phase will never succeed in such cases; in order to enhance the robustness of the phase selection scheme, it is thus necessary to optionally choose both the number and the type of features with the development of the scheme, concomitant with the employment of a pattern recognition technique such as AI, as discussed later.

4.3 Summary

In this chapter, different faults at different fault inception angles and locations are simulated in section 4.1. Even though there are similarities among different scenarios, significant differences can be seen among all the faults simulated. The fault currents need to be pre-processed before it can be utilized for realizing the protection scheme.

Also, the main information shown in the results is dominated by the power frequency components and the transients are not clearly discernible due to their higher frequencies and much smaller magnitudes. A tool that can decompose the original waveforms and extract the transient information is hence required, in order to provide a solid base for developing the transients based protection scheme.

In section 4.2, the simulated fault current data is analysed using the WT and the fault transients is extracted and the features optimised as a prerequisite in the development of the protection scheme. It mainly describes the methods for the feature extraction step of the protection scheme based on the WT. The principle as to reason why this approach adopted is further explained. More details about the principle of the wavelet are introduced as well as the reason for choosing one particular mother wavelet. Then WT is used to decompose the fault current signal for different fault
conditions (type, inception angle and distance) and the spectral energy details of the WT coefficient are calculated. Finally, the results from the process are analyzed and compared. A few points can be summarized below:

1) The WT can extract the fault transient information from the fault current signals.
2) The spectral energy of the wavelet coefficients needs to be used instead of the coefficients themselves.
3) With the application of the WT decomposition and the calculation of the spectral energy, the feature that differentiates the faulted phase from healthy phases is more outstanding.
4) The post-processed data under different fault scenarios has also shown that:
   a) For the same fault type, the peak spectral energy value are significantly different at different fault inception angles
   b) In some cases, the healthy phase has comparable energy level as the faulted phases at the fault inception point

The two situations may cause difficulties in realizing accurate phase selection schemes.

In summary, the great advantage of the WT analysis is realized but the difficulty to develop a scheme that applies to all the fault situations is also apparent. Next chapters introduce the methodology to realize the protection by using artificial intelligence techniques to overcome the aforementioned difficulties.
Chapter 5 Artificial Intelligence Techniques and the Development of the Phase Selection Scheme

5.1 Introduction

The most important features of the fault transients from the current signals for different fault occasions in the simulated 400 kV UK transmission system are identified and extracted using the WT, as shown in the last chapter; they will be further utilized herein to effect the decision-making processes and the artificial intelligence techniques, viz., fuzzy logic (FL) and artificial neural network (ANN) methods are chosen for this purpose.

This section firstly reviews the reasons for adopting AI techniques in the protection scheme developed herein, followed by a detailed introduction to FL and ANN, respectively and the methodology developed based on the latter. Different types of FL and ANN are introduced and discussed in detail. After an extensive series of studies, near optimal types are chosen. Then one type of each technique is chosen to effect a phase selection scheme, as the first stage of the overall protection scheme. The architecture of the phase selection is proposed and briefly discussed. Lastly, the results from the scheme for different faults are illustrated and discussed.

5.2 Motivation to use AI techniques

As introduced in the last chapter, even though by using the WT analysis, the most important features that need to be dealt with can be extracted, there are still complexities of the processed information that cannot be handled using traditional mathematical techniques. To handle such a set of data to effect a robust decision making algorithm, the tool is expected to have the following features [18]:

a.) further simplification of data structures when necessary

b.) handle the non-linear relationship between the inputs and outputs

c.) handle the extraneous noise that is usually present in the signals, i.e. to make the developed technique immune to such noise
d.) Able to learn from the examples and re-produce the results of the examples

e.) Able to achieve the analysis results efficiently.

Based on the above discussion, artificial intelligence techniques FL and ANN which are well known in pattern recognition and predictions, parallel processing and non-linear mapping are best suited tools to serve this purpose.

AI technology has become increasingly popular in the power system application in recent years due to its capability of handling complicated power system and achieving fast and accurate results. These are reported in the following literature [8, 16, 38-40]. And aspects of it are adopted in the methodology developed herein to achieve the best outcomes.

5.3 AI Techniques Introduction

AI techniques comprise of a collection of very powerful tools, such as ANN, expert system, FL etc. ANN was already briefly introduced and reviewed in chapter 2 of this thesis, and more details about FL and ANN will be discussed here respectively.

5.3.1 Fuzzy logic

Fuzzy logic deals with approximate (fuzzy) reasoning rather than exact reasoning, i.e., it can handle a degree of uncertainty with regard to its input and output relationships. Input and output values are processed by so-called fuzzification and de-fuzzification stages respectively – the output values usually vary in a universe of discourse suitable for the particular problem being handled [26].

For a FL system, the critical thing is to choose an appropriate membership function (MF), which handles and defines the fuzzification of the real world inputs and transforms them into outputs. MF is used to map the points in the input space to membership values, e.g. between 0 and 1. MF can usually be represented by a curve [26].

As mentioned in the last chapter, though the energy of the faulted phase shows a distinct feature over the healthy phases, but the absolute values between different fault scenarios, especially at different inceptions angles, are significant. Due to this
scaling problem of the data, some initial trials of the ANN failed to predict either the faults at 90° or the faults at 0° inception angle.

FL provides a solution to cope with this scaling. Based on the maximum energy value, it can turn all the energy values into the domain of 0 and 1 with an appropriate membership function. It is selected to reduce the difference between different fault inception angles thereby keeping the classified feature between the faulted phase and healthy phases.

Based on the FL principle and due to the fact that the parameters are simple, S-shaped built-in membership function is used to convert the previously described extracted features into fuzzy sets that are taken as the inputs for the neural network. The S-shaped membership function is defined as shown in eqn 5-1. The left and right extreme locations of the function are defined by ‘a’ and ‘b’ [26]. At the left side, the value of the function is 0 and at the right side, the value of the function is 1.

\[
f(x; a, b) = \begin{cases} 
0, & x \leq a \\
\frac{1}{2} \left( \frac{x-a}{b-a} \right)^2, & a \leq x \leq \frac{a+b}{2} \\
1 - \frac{1}{2} \left( \frac{x-b}{b-a} \right)^2, & \frac{a+b}{2} \leq x \leq b \\
1, & x \geq b 
\end{cases} 
\]

\text{eqn 5-1 [26]}

For example, when x is from 0 to 10 (interval is 0.1) and a=1, b=8, we can get a result as shown in Figure 5-1.

![Figure 5-1 Example of S-shaped membership function [26]](image)
In the work presented herein, x is the spectral energy which is calculated at the feature extraction stage and parameter ‘a’ equals to 0 as a direct consequence of the minimum magnitude of the phases’ energies being nearly 0. Parameter ‘b’ equals the maximum value of the spectral energy because the maximum value appears in the faulted phases at fault inception point and hence the fuzzificated data of faulted phases at that point will be 1.

5.3.2 Artificial Neural Networks (ANN)

The results from the FL stage then become inputs into the ANN for the final decision making in the scheme. The decision making stage for the scheme is actually a kind of pattern recognition problem, i.e. the detection of the fault and the identification of the fault type need to be made when the inputs (features of the fault current transients) are provided. ANN can map complex nonlinear patterns and also it has a large feature space which can cover different fault conditions and system configurations, which can make the phase selection scheme work accurately and efficiently.

The neural network technique functions are somewhat similar to the human biological nervous system, which consists of parallel operating neural elements that acquire inputs from the external environment (e.g. information/data) and generate outputs to it as a response (e.g. action/data). It is based on an analogy of the way that is believed to be how the human brain works. Essentially, it has lots of processing units, which are simple individually but are able to achieve a very complicated function (decision making, judgement and response etc.), after they are connected together as a nervous network or system. The full mechanism behind it is still being heavily investigated by the neuroscience researchers[18].

The single-neuro model used here is a simplified representation of the real human brain neuron. It is shown in Figure 5-2 x₁ to xₚ is the input and yₖ is the output. uₖ is the real input for the neurons and it can be achieved using the following equation[18]

$$u_k = \sum_{p=1}^{n} w_{kp} x_p$$  \hspace{1cm} \text{eqn 5-2 [18]}

wₖₚ is the weighting factor, n is the number for the inputs and k is the specific neuron.
The function used in the neuron to generate the output $y_k$ is called activation function. It can be described as below:

$$y_k = f(u_k - \theta_k) = f\left[\sum_{p=1}^{n}(w_{kp}x_p - \theta_k)\right] \quad \text{eqn 5-3 [18]}$$

$\theta_k$ is a threshold which is used to lower down the network output of $y_k$. As can be seen from the formula, both the weighting factor and the threshold have a direct impact on the output. Activation function, on the other hand is very critical. There are basically three types of the activated function used broadly, the formula of which are shown in Table 5-1 [18] and their variation with $u$ are demonstrated in Figure 5-3. The sigmoid function is the mostly common used one in ANNs [18].

It can be seen from the above equations, with different weighting factors, each neuron element will play a different role in the network. These weighting factors are determined by how the network is trained based on a particular purpose. Training an ANN actually means to adjust the weights for the respective neuron, i.e. how to distribute the importance of each element to realize certain functions as requested[18].

**Table 5-1 Activation Functions [18]**

<table>
<thead>
<tr>
<th>Function Type</th>
<th>Expressions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Threshold</td>
<td>$f(u) = \begin{cases} 0, &amp; u \leq 0 \ 1, &amp; u &gt; 0 \end{cases}$</td>
</tr>
<tr>
<td>Piecewise-linear</td>
<td>$f(u) = \begin{cases} 0, &amp; u \leq -0.5 \ u, &amp; -0.5 &lt; u \leq 0.5 \ 1, &amp; u &gt; 0.5 \end{cases}$</td>
</tr>
<tr>
<td>Sigmoid</td>
<td>$f(u) = \frac{1}{1 + e^{-10u}}$</td>
</tr>
</tbody>
</table>
As shown in Figure 5-4, the neural networks are usually trained in a way that an input leads to a needed/required target output. The training of ANN is generally an iterative process and can only be considered as completed or successful when certain output target / convergence criteria are met. When this is not met, the weights of the neural elements will be adjusted and the whole process will be repeated. Obviously, for the training stage, both of the inputs and outputs (targets) are given. Generally speaking, a good amount of inputs and outputs will be required to train a proper neural network that provides accurate results[18].
The neural network structure is directly influenced by the specific problem. Feedforward layered network (FLN) has been used by many researchers as they can map the nonlinear input/output patterns with high learning accuracy and they are easy to implement; therefore it is chosen for this project. The ANN technique has demonstrated its ability in terms of non-linearity, generalization, prediction capability and for handling complex interactions of the input variables [60]. It is one of the most effective types of neural networks for pattern recognition.

Figure 5-5 shows how a general three-layer feedforward neural network looks like. It is composed of input layers, hidden layers and output layers. There is usually only one input layer and one output layer while there can be more than one hidden layer. Elements in the input layer and output layer are problem specific while hidden layers
are the real units that are trained and functioning as neural that generates the results. In a neural network, when all the layers are properly used, it can learn to classify and analyse the inputs as desired.

To train an ANN to serve specific purpose, certain learning rules need to be followed. Feed forward networks are trained by the method of supervised learning. Supervised learning consists of presenting examples of the problem to be solved to the network along with a required ‘answer’. Various algorithmic training methods exist for using the difference between the required and the actual output from the network to train the network.

The steps for using Multilayer feedforward neural network are [18]:

Step 1: Select input. Feature extraction is usually the first step for pattern recognition problems. The performance and size of the ANN are dependent on the selected inputs/features.

Step 2: Gather data for training. Supervised learning is used for this type of ANN; therefore, appropriate training data is imperative.

Step 3: Select ANN. The number of inputs, hidden neurons and hidden layers need to be determined.

Step 4: Train ANN. Train the ANN until the optimal performance is achieved.

Step 5: Test ANN. Use the data which are not used for training, to test the ANN.

It is suggested in [18], to get the optimal results of the ANNs, three conditions should be satisfied. The first one is that the input data of ANNs should contain the featured information which is the most important thing in pattern recognition. Secondly, a proper neural network topology needs to be chosen. Finally, the optimal number of hidden layers should be set and various training networks should be tested to get the optimal number of neurons in the hidden layer. In this project, an extensive series of studies revealed that only one hidden layer was sufficient to cater for the vast majority of different system and fault conditions.
The first task of the scheme is to be able to distinguish clearly the occurrence of a fault and the type of the fault, i.e. to realize the phase selection function. It is worthwhile to mention here again, the four typical types occur on a power transmission system are:

a) Single-phase to ground fault  
b) Phase-to-phase fault  
c) Double-phase to ground fault  
d) Three-phase to ground fault

There are the three phases and the ‘ground’ that need to be considered in a fault and hence there are four outputs for the ANN and they are represented by A, B, C, G, which signify phase A, Phase B, Phase C, and ground respectively. As for the values, when the phase has a fault, it is represented by ‘1’ and when the phase is healthy, it is represented by ‘0’. Likewise, when a ground is involved in a fault then the value of G is 1, 0 otherwise.

5.4 FL and ANN based Phase Selection scheme

5.4.1 Overview

In the work presented herein, the development of the phase selection scheme is the first stage and also it is the pre-requisite for the development of the next stage: fault detection for the internal and external fault. An accurate and robust phase selection technique is thus crucial to the overall performance of this complete protection scheme.

The phase selection scheme is illustrated in Figure 5-6 as a flow chart. As can be seen, the fault signals of the currents are firstly simulated. Then at the feature extraction stage, the current signals are processed by the WT decomposition. Further, the spectral energy of the combined detail (as discussed later) is calculated for each phase by a moving time-domain window of length 20 samples (1.2ms) with no overlap and then fuzzy membership function is used to generate fuzzy sets for each window of spectral energy. The fuzzy sets are then input into the ANN for training and testing. The data generated from the feature extraction is split into two sets. One
is for training and the other is for testing. After that, appropriate ANN is trained and tested so that the faulted phase selection function can be realised.

![Flow Chart for FL and ANN based Phase Selection Scheme](image)

**Figure 5-6 Flow Chart for FL and ANN based Phase Selection Scheme**

### 5.4.2 The selection of Detail energy

It is clearly evident that the maximum spectral energy appears at fault inception point for both 90° and 0° inception angle due to the fault generated high frequency component. As shown in these figures, the magnitude of the spectral energy at the fault inception point of the faulted phase is much greater than healthy phases. But when all the fault types at different fault inception positions and fault inception angles are considered, it is not always perfectly true. To extract the most useful information to realize accurate phase selection, two requirements for detail energy selection should be satisfied.

1) The maximum detail spectral energy of phase should occur at the fault inception point
2) The maximum detail spectral energy of faulted phase should be much higher than healthy phase

Based on these conditions, a comparison of the detailed energies for different fault types, fault inception angles and fault inception positions have been made and it has been found that the energy of the combination of both D2 and D3 gives the best results for this work; hence this combination is chosen in the development of the phase selection scheme.

5.4.3 Fuzzy Logic Application

As mentioned above, a combination of detail spectral energy D2 and D3 have been chosen for this project. It should also be noted that in Figure 5-7, the difference in the maximum energy magnitudes of the faulted phase for different fault inception angles is significant (2×10^5 for 90° inception angle and 140 for 0° inception angle); this can cause problems for the ANN to realise phase selection. The reason is that, when an ANN is trained, the desired output is 1 when the input is of the maximum magnitude, i.e. in the case when the input of magnitude is 2×10^5. However, for the significantly lower input of 140, the ANN will have difficulty in identifying the correct faulted phase(s), i.e. make the right decision; this can be attributed to the fact that the ANN swaps over the higher magnitude input related decision over the lower magnitude input, particular during the training process, i.e. the characteristics associated with the latter are lost. Hence, to improve the performance of the ANN, FL is employed to solve this problem.

As discussed earlier, the S-shaped membership function is applied to the 4-level spectral energy information (D1-D4) from the wavelet transformation. Figure 5-7 to Figure 5-9 gives a comparison of the three-phase data before (spectral energy) and after (fuzzification data); the membership function is used for both 90° and 0° fault inception angles. They are AG faults at 32km.

It is apparent from Figure 5-7 that before the application of the FL, the difference in the spectral energy levels for the two fault inception angles, viz. 90° and 0° is very large however after fuzzification, the levels become comparable. When these data is imported into the ANN, it can give correct outputs for both high- and low- value data.
Figure 5-8 and Figure 5-9 show similar situation as Figure 5-7 for the healthy B and C phases for the same fault. The maximum values for the fuzzified data are close to zero and this indicates that they are healthy phases.

The foregoing clearly demonstrates that, the problem of large differences between maximum and minimum spectral energy level can be solved using the FL application. This is an additional stage that has to be developed after the feature extraction stage and the output will be used as the input to the ANN.

There is another issue that the maximum spectral energy must be known before the FL membership function can be applied but in reality, this is impossible. Other techniques need to be examined to overcome this problem and this is discussed in the next chapter.

![Figure 5-7 Comparison of spectral energy and fuzzified data of A phase for AG fault at 32km (fault inception angle=90° and 0°)](image-url)

Figure 5-7 Comparison of spectral energy and fuzzified data of A phase for AG fault at 32km (fault inception angle=90° and 0°)
Figure 5-8 Comparison of spectral energy and fuzzificated data of B phase for AG fault at 32km (fault inception angle=90° and 0°)

Figure 5-9 Comparison of spectral energy and fuzzificated data of C phase for AG fault at 32km (fault inception angle=90° and 0°)
5.4.4  Neural Network Architecture and Training

The fault current data cover a wide range of different system and fault conditions such as fault inception angles, fault locations and faulted types, to ensure the phase selection scheme is generalized. Once the sets of training/testing patterns have been generated through WT and FL, an appropriate ANN architecture and associated parameters must be chosen for the particular application.

The task of ANN is to learn to capture these common underlying characteristics of input data to select the faulted phase(s). Through a series of tests and modifications, it has been found that the network topology presented in Figure 5-10 shows a near optimal performance for this particular application. It is a three-layered network which consists of 3 inputs in the input layer, 16 nodes in the hidden layer and 4 outputs in the output layer. The details of input, and target output of ANN are shown below.

**Inputs:** 3 inputs corresponding to 3 phases’ fuzzificated energy data from the FL and WT

**Target outputs:** 4 target outputs are defined as examples shown below.

<table>
<thead>
<tr>
<th>Fault Type</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>G</th>
</tr>
</thead>
<tbody>
<tr>
<td>AG</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>BG</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Where ‘A’, ‘B’ and ‘C’ refer to A phase, B phase And C phase of the transmission line separately; in the case of G, 0 signifies that ground is not involved in a fault and 1 means that it is.
When the training data has been scaled to the appropriate range by the application of FL, it is presented to the ANNs randomly; this is vitally important because sequential presentation may make the ANN either to converge very slowly or in some cases to diverge as a result of forgetting what it had learnt previously [60].

Figure 5-11 shows the variation of mean square error (MSE) during the training for an ANN, corresponding to a set of inputs and a set of expected outputs. When the MSE from the validation reaches the best performance (i.e. lowest value of MSE), the training process stops and the ANN has the optimum weighting factors for its nodes.
Figure 5-11  MSE variation for the Training of an ANN

5.5 Results and Discussion

Following the training of the ANN, a separate set for testing was supplied as input to the ANN in order to evaluate its performance. Figure 5-12 and Figure 5-13 show the output of ANN for test data for an AG fault at 32km at a fault inception angle of 90° and 0° respectively. It can be seen that, the actual outputs of ANN for both cases are ‘1 0 0 1’ corresponding to ‘A B C G’ (because the output values of healthy phase are so small, they are taken as 0). This means that ANN can accurately classify the faulted phase (A) from the healthy phases (B and C) in the extreme fault inception angle cases.

To prove the efficiency of the phase selection scheme, more test results are shown in Table 5-3. The left three columns of the Table are the desired outputs; ideally ‘1’ or ‘0’ and the right three columns are the actual outputs of the ANN. In each case, the fourth column signifies the presence of ground in a fault. It is apparent that the trained ANN responds correctly to all the various fault types and conditions considered.
Figure 5-12 Actual output of ANN for test data of AG fault at 32km (fault inception angle=90°)

Figure 5-13 Actual output of ANN for test data of AG fault at 32km (fault inception angle=0°)
Table 5-3 Test results of neural network

<table>
<thead>
<tr>
<th>Desired output</th>
<th>Actual output</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fault type</strong></td>
<td><strong>A</strong></td>
</tr>
<tr>
<td>AG 12km(90°)</td>
<td>1</td>
</tr>
<tr>
<td>AG 64km(90°)</td>
<td>1</td>
</tr>
<tr>
<td>AG 108km(0°)</td>
<td>1</td>
</tr>
<tr>
<td>BG 32km(90°)</td>
<td>0</td>
</tr>
<tr>
<td>CG 96km(0°)</td>
<td>0</td>
</tr>
<tr>
<td>AB 32km(90°)</td>
<td>1</td>
</tr>
<tr>
<td>BC 12km(90°)</td>
<td>0</td>
</tr>
<tr>
<td>BC 64km(0°)</td>
<td>0</td>
</tr>
<tr>
<td>BC 108km(90°)</td>
<td>0</td>
</tr>
<tr>
<td>AC 96km(0°)</td>
<td>1</td>
</tr>
<tr>
<td>ABG 12km</td>
<td>1</td>
</tr>
<tr>
<td>BCG 20km</td>
<td>0</td>
</tr>
<tr>
<td>CAG 12km</td>
<td>1</td>
</tr>
<tr>
<td>CAG 64km</td>
<td>1</td>
</tr>
<tr>
<td>CAG 108km</td>
<td>1</td>
</tr>
<tr>
<td>ABCG 32km</td>
<td>1</td>
</tr>
</tbody>
</table>
5.6 Summary

A phase selection scheme based on WT and AI techniques is proposed and demonstrated in this chapter. In response to the two problems identified from the last chapter, two measures are taken.

- For the scaling problem of the data at different inception angle, FL is employed.
- For the anomaly in the spectral energy data among the healthy and faulted phases, an spectral energy combination of D₂ and D₃ is employed as the input.

It is demonstrated that the two aforementioned measures can help solve the problem of the data and lead to satisfactory results for the phase selection based on the employment of ANN for the decision making process.

However, the method presented herein also adds one intermediate step (FL) in the scheme between WT and ANN; this requires more computational resources and adds to the cost to realise the scheme. Furthermore, FL always requires that the maximum values of the coefficients/energy to be known beforehand, which is usually not possible unless the fault has already happened. Hence, this method cannot be used in reality and a more generalized way is required. This is further discussed in the next chapter.
Chapter 6  Current Based Phase Selection and Fault Detection Scheme and Case Studies on UK 400kV EHV Transmission Line

6.1 Introduction

Based on the methods and techniques presented so far in this work, this chapter describes a novel phase selection and fault detection scheme using current signal data from only one end of a transmission system to realise the overall power system protection scheme. Firstly, the measured current signals are decomposed using the WT to obtain the necessary frequency details and then the spectral energy for a chosen number of wavelet coefficients are calculated using a moving short time window; this forms the feature extraction stage, which in turn, defines the inputs for the ANN which is used for classifying the types of fault. The input features comprise both the high frequency (HF) and low frequency (LF) components to enhance the performance of the scheme. This is different from the methodology described in the last chapter, where only high frequency components are used and a transition stage (FL) is required to achieve high accuracy.

After the fault type is identified, the proposed scheme selects the specific ANN based on the fault type to distinguish between internal and external faults by utilizing the same pattern features extracted from the previous stage. It should be mentioned, the work presented in this chapter is principally based on the author’s conference paper [61], presented at the IEEE PES meeting, San Diego, USA, July, 2012.

6.2 System Model and Fault Simulation

The simulation of the power system has been carried out using the EMTP software as introduced in chapter 4. It is briefly reviewed here with regard to the parameters for the simulated EHV transmission line.

The EHV transmission line is based on a single circuit of the typical 400 kV UK transmission line. It consists of two sources connected by a three phase transmission line of a typical length of 128 km. The capacity of each source is 5 GVA. Busbar capacitor is selected as 0.1μF. The power system frequency is taken to be 50 Hz. The
fault resistance to ground is taken to be $2 \Omega$ and the fault resistance is $0.001 \Omega$. Figure 6-1 again typifies the power system studied. An X: R ratio of 100 was used for each source terminating a busbar. The simulation is based on a sampling frequency of 16 kHz.

![Power system model](image)

**Figure 6-1 Power system model**

As stated in chapter 4, extensive simulation studies for fault currents have been carried out based on this transmission line model using the EMTP software. The original current waveforms for single-phase to ground, phase-to-phase, double-phase to ground and three-phase to ground faults have been simulated at different fault locations and different fault inception angles for developing and testing the phase selection and fault detection scheme in this chapter.

### 6.3 Implementation of the Protection Scheme

#### 6.3.1 Overview

The framework of the complete protection scheme is illustrated in Figure 6-2. The three-phase currents are obtained at the sampling rate 16 kHz. This is because higher sampling frequency means more burden on the processing power of the digital processor and lower sampling frequency will not capture the requisite transients. As discussed, through the signal processing stage, current signals are decomposed by the DWT and then the spectral energy of each coefficient is extracted using a sample window of 20 samples (approx. 1.2ms). At the feature extraction stage, i.e. the first stage, low and high frequency wavelet energy coefficients are chosen. Through an
extensive series of studies, the most appropriate features based on the energy coefficients and the associated spectral energy are then chosen as input features for training a single ANN, for phase selection. Ten ANNs (three for single-phase to ground faults, three for phase-to-phase faults, three for double-phase to ground faults and one for three-phase to ground fault), are also trained individually to cater for fault detection. Based on the output of the phase selector, the appropriate ANN is then enabled at the fault detection stage. FL as discussed previously is not necessary any more due to a more appropriate selection of the features that feeds into the ANNs.

![Figure 6-2](image.png)

**Figure 6-2 The Protection Scheme Framework**

### 6.3.2 Feature Extraction

Fault current signals are generated through the simulation of the power system and are then applied to the feature extraction stage to capture the most significant fault information contained in the fault current.

As already discussed previously, feature extraction is an extremely important stage in a pattern recognition method as it effectively reduces the size of the ANN that has a
large feature space and can be used for developing the protection scheme under different system and fault conditions to achieve the desired performance. Fault generated transients used in this protection scheme contain a wide range of frequency components. Therefore, it is impractical to use the time-domain signals directly as the inputs to an ANN because it is very time consuming and a large amount of data is needed for training. Furthermore, high accuracy is hard to achieve. Therefore, it is necessary to extract the most significant features from the original data so that the amount of training data can be reduced without compromising the accuracy.

The features used as inputs of the ANN are extracted from a moving window of 20 samples and there is no overlap between two subsequent windows. At every time step, the three-phase current signals are sent to the WT decomposition stage and then spectral energy for every WT coefficient is calculated by the moving window. It should be noted that, the feature extraction process for both phase selection and fault detection is the same, thereby saving computational time.

6.3.2.1 Wavelet Transform and Spectral Energy

In the protection scheme described herein, the WT is applied to decompose the current signals into a series of detailed wavelet components, each of which is a time-domain signal that covers a specific frequency band. The Db4 mother wavelet has been chosen in this project as it can very effectively deal with signals which are of low amplitude, short duration and fast decaying [62]. Its capability has already been demonstrated in section 4.2.1.3.

To enhance the features information, the spectral energy of the coefficients at each level is calculated based on eqn 4-5 in Chapter 4. This has been already discussed in section 4.2.1.4 and it will not be repeated here.

6.3.2.2 Selection of Decomposition Levels as Input for ANN

As phase selection is performed before fault detection, decomposition levels are firstly chosen for phase selection. It is proposed here that, to extract the most efficient details for optimizing the results of the ANN training/testing, the following criteria should be considered:
To be able to clearly distinguish fault inception time; the maximum detail energy should occur at the fault inception point

To be able to distinguish faulted phase(s); the maximum detail energy of the faulted phase(s) at the fault inception point should be much higher than the healthy phase(s)

To be able to make sure the proposed scheme works well under both 90° and 0° fault inception angles, chosen details should contain similar characteristics for both scenarios.

Figure 6-3 typifies the fault current waveforms simulated for an AG fault at 90° inception angle and at 64 km from the sending end.

Based on the aforementioned considerations and extensive series of studies, ten-level wavelet decomposition components of three phase currents are chosen for the proposed scheme. In Figure 6-4, when the fault inception angle is 90°, comparing the magnitudes of the signals of the various levels, it is apparent that those associated with the faulted A-phase are significantly higher than those for the B and C phases (which are not discernible in the figure) and this is a clear indication that it is the A-phase that is the faulted phase. Although not shown here, the signals for the three phases behave similarly when the fault inception angle is 0°.

Comparing the wavelet coefficients of decomposition for both voltage 90° and 0° fault inception angles, it is evident from Figure 6-5 that in the case of the 90° faults, the magnitude of the coefficients for levels 1-5 (i.e. the higher frequency spectrum end) are much bigger that those associated with the voltage 0° faults. However, for voltage 0° faults, it is the coefficients at the lower frequency end of the spectrum (i.e. levels 6-10) that are accentuated significantly compared to those associated with the voltage 90° faults. This unique characteristic offers an opportunity to make the proposed scheme work well for both extreme situations i.e. inception angles of 90° and 0°.

A series of studies have shown that the decomposition up to level 10 is near optimal for maintaining the ANN’s accurate performance and further decomposition is unnecessary.
For the fault detection, the directional protection principle based on current in [14] is only effective in a frequency range above 1 kHz. However, from a practical point of view, more low frequency details which contain other useful features need to be considered. Based on the proven ten-level wavelet decomposition, spectral energy details of ten levels for internal and external faults are shown in Figure 6-6. It is apparent from this figure that for the majority of different levels, the magnitudes of the spectral components are larger for internal faults compared to external faults. A similar phenomenon is observed when the fault inception angle is changed to 0°. This is so because external fault transients are affected by transmission line shunt capacitance and this attribute allows the features shown in Figure 6-6 to be used to distinguish between internal and external faults.

![Image](image.png)

**Figure 6-3** Three phase current waveforms of an AG fault at 64 km from the sending end (fault inception angle 90°)
Figure 6-4 Ten level spectral energy details of the three phase current of an AG fault at 64 km from the sending end (fault inception angle 90°)

Figure 6-5 Ten level spectral energy details of the A phase of an AG fault at 64 km from the sending end (fault inception angle 90° and 0°)
It should be noted that when the energy information is used in ANN, the accumulated spectral energy signal is used instead of the energy for each window to achieve better performance, i.e.:

\[ E_j(k) = \sum_{n=1}^{20k} cD_j(n)^2, \quad k = 1,2,3,... \quad \text{eqn 6-1} \]

i.e. eqn 7-1 is employed instead of previously derived eqn 4-5.

### 6.3.3 ANN Architecture and Training

ANN is used for decision making to enhance the performance of the scheme. The reason why ANN was chosen over other techniques was already discussed and analysed in details in the last chapter. Here the focus is on how it is trained and how the final architecture is determined in the phase selection scheme and the fault detection scheme, respectively.
6.3.3.1 ANN for Phase Selection - Training and Testing

Fault scenarios are generated for the system shown in Figure 6-1 using EMTP and MATLAB is used for the data post-processing[63]. There are 256 fault cases taking into account: ten types of fault including single-phase to ground, phase-to-phase, double-phase to ground and three-phase to ground fault; 16 fault locations - one at every 8km interval from the sending end; two fault inception angles (0° and 90°). All fault cases with the exception of faults at 12km, 72km, and 116km fault locations (they are used for testing) are used to train the ANN.

Through a series of tests and modifications, it has been found that the ANN presented in Figure 6-7 gives a near optimal performance for this particular application. It is a three-layered network which consists of 30 inputs in the input layer, 20 nodes in the hidden layer and 4 outputs in the output layer. Details of the input and target output of the ANN are:

**Inputs:** 30 inputs which are ten-level accumulated energy of WT decomposition of 3 phase current components

**Target outputs:** 4 target outputs are defined and the examples are shown in Table 6-1. In the table, A, B, C and G refer to A phase, B phase, C phase and ground respectively. ‘1’ implies A phase (or ground) is involved in a fault and ‘0’ signifies otherwise.

The example of the inputs and target outputs for one ANN in the signal format are shown in Figure 6-8 and Figure 6-9, respectively. It is apparent from both figures that the accumulated energy keeps almost constant after the fault inception point. This is due to the application of the accumulated energy (eqn 6-1) instead of the individual energy for each window. This type of behaviour is more in accordance with the simulated system than the one shown earlier, since the fault maintains itself after the fault inception point in the simulation, i.e. the target output should be always be 1 after the occurrence of the fault in the cases studied herein.
Figure 6-7  ANN-topology for the Phase Selection Scheme

Table 6-1 Ten Fault Types and the Target Outputs

<table>
<thead>
<tr>
<th>Fault Type</th>
<th>Target Outputs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
</tr>
<tr>
<td>AG</td>
<td>1</td>
</tr>
<tr>
<td>BG</td>
<td>0</td>
</tr>
<tr>
<td>CG</td>
<td>0</td>
</tr>
<tr>
<td>AB</td>
<td>1</td>
</tr>
<tr>
<td>CA</td>
<td>1</td>
</tr>
<tr>
<td>BC</td>
<td>0</td>
</tr>
<tr>
<td>ABG</td>
<td>1</td>
</tr>
<tr>
<td>CAG</td>
<td>1</td>
</tr>
<tr>
<td>BCG</td>
<td>0</td>
</tr>
<tr>
<td>ABCG</td>
<td>1</td>
</tr>
</tbody>
</table>
6.3.3.2 ANN for Fault Detection - Training and Testing

After the type of the fault is determined by the phase selection, the appropriate ANN concerning with a particular fault type will be involved to make a decision for the fault detection. Ten ANNs corresponding to ten fault types are trained separately using different data in different fault situations.
It is found that the ANN topology shown in Figure 6-10 gives a near optimal performance for the application. It is a very similar network compared to what is used for the phase selection scheme and has N nodes in the hidden layer (N varies from 18 to 20 depending on the fault type) and one output node.

![ANN-topology for Fault Detection](image)

**Figure 6-10  ANN-topology for Fault Detection**

It should be mentioned that herein, the same training and test data employed in the phase selection ANN is used for internal faults while additional fault training and test data are generated for external faults. The details of input, and target output of the ANN are shown below.

**Inputs:** 30 inputs which are ten level accumulated energy of WT decomposition of 3 phase current components for one type of fault

**Target outputs:** 1 target output is defined and the examples are shown in Table 6-2.

It should be mentioned that in the process of fault detection, there is a very important criterion to distinguish accurately between internal and external faults and no fault cases. A series of studies have shown that a high weighting of 10 associated with the ANN for internal faults is the near optimal option for the precise discrimination between faults, principally internal and external faults. Likewise, the target output of 1 for external fault is necessary to distinguish external fault and non-fault situation.
Examples of input and the corresponding output for the internal faults are shown in Figure 6-11 and Figure 6-12 respectively. Those for external faults are shown in Figure 6-13 and Figure 6-14.

Table 6-2 Fault type examples

<table>
<thead>
<tr>
<th>Fault type</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Internal fault</td>
<td>10</td>
</tr>
<tr>
<td>External fault</td>
<td>1</td>
</tr>
<tr>
<td>Non-fault</td>
<td>0</td>
</tr>
</tbody>
</table>

Figure 6-11 Example of Inputs: Accumulated Energy of D₁ of phase A for AG internal fault at 48km from the sending end, 90°
Figure 6.12 Example of target outputs: for AG internal fault

Figure 6.13 Example of Inputs: Accumulated Energy of D₁ of phase A for AG external fault at the sending end, 90°

Figure 6.14 Example of target outputs: for AG external fault
6.4 Results and Discussion

6.4.1 Phase Selection Results and Discussions

Following the training of the ANN, the separate set of test data mentioned before was supplied to test the trained ANN in order to evaluate its performance. The test results for various fault locations, fault inception angles and fault types are shown in Table 6-3 to Table 6-5.

6.4.1.1 Effect of Fault Position

In this part, various fault positions (12km, 72km, 116km from the sending end) are tested respectively. Results in Table 6-3 prove that this phase selection is immune to fault locations. Figure 6-15 shows how the real outputs from the ANN are similar for the AC fault at 116km (90° inception angle) as an example. It also shows that the scheme accurately predicts the fault occurrence time as well as the fault type.

![Figure 6-15 ANN actual output for AC fault at 116km, 90°]
### Table 6-3 Results for various fault positions (Fault inception angle: 0° for CG and BC fault)

<table>
<thead>
<tr>
<th>Fault locations</th>
<th>Fault types</th>
<th>Desired output</th>
<th>ANN output</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>B</td>
<td>C</td>
</tr>
<tr>
<td>12 km CG</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>72 km CG</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>116 km CG</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

### 6.4.1.2 Effect of Fault Inception Angle

Fault inception angles of 0° and 90° are the two extreme situations in terms of fault inception angles. In this work, to identify the robustness of the phase selector, faults for the two inception angles are tested and the results are shown in Table 6-4. It is apparent that even when fault inception angle is 0°, the proposed phase selector can accurately select the faulted phase(s). It also proves that the method proposed earlier (to use both the HF and LF information from ten-level WT decomposition) to solve the data scaling problem between the two extreme fault inception angles works very well.
Table 6-4 Results for various fault inception angle (Fault location: 116km)

<table>
<thead>
<tr>
<th>Fault inception angle</th>
<th>Fault types</th>
<th>Desired output</th>
<th>ANN Actual output</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>0°</td>
<td>AG</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>AB</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>BG</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>BC</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>CG</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>AC</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>90°</td>
<td>AG</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>AB</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>BG</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>BC</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>CG</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>AC</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

6.4.1.3 Effect of Different Fault Types

Ten types of fault including single-phase to ground, phase-to-phase, double-phase to ground and three-phase to ground faults are tested and the results shown in Table 6-5
clearly prove that the proposed phase selector performs accurately under different fault types.

Table 6-5 Results for various fault types (Fault inception angle: 0° and fault location: 72km)

<table>
<thead>
<tr>
<th>Fault types</th>
<th>Desired output</th>
<th>ANN output</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>AG</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>BG</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>CG</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>AB</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>AC</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>BC</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>ABG</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>ACG</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>BCG</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>ABCG</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

6.4.2 Fault Detection Results and Discussions

As mentioned before, although the criteria for distinguishing non-faults, external and internal faults are based on the ANN output ‘0’, ‘1’ and ‘10’ respectively in Table 6-2, however extensive series of studies have shown that from a practical point of view, the optimal thresholds herein for clearly distinguishing the three types of fault are as shown:
if the output is less 0.5, then reset output to be 0, indicating non-fault;
if the output is greater than 0.5 but less than 5.5, then reset output to be 1, indicating external fault;
if the output is greater than 5.5, then reset output to be 10, indicating internal fault;

For a specific fault, if the ANN output continuously satisfied the aforementioned threshold levels for 8 samples, then it will be identified as an external or an internal fault. This can also improve the robustness of the decision making process. The MATLAB program to realize this is shown in the appendix B. The test results are discussed below.

6.4.2.1 Typical Response to Internal and External Faults

Figure 6-16 shows the responses of the proposed algorithm to both internal and external faults. From Figure 6-16 (a), it is apparent that at the fault inception point, the ANN output quickly settles to a level near 10 and it is classified as an internal fault. This is in marked contrast to the ANN response for external faults shown in Figure 6-16 (b) and (c). Here the outputs are significantly less than 10 (between 1 and 2) and remain so at these low levels for an appreciable time after fault inception, thereby signifying an external fault.
6.4.2.2 Effect of Inception Angle

It is well known that faults occurring near voltage maximum giving rise to the largest travelling waves than those near voltage zero [64]. In other words, high frequency fault transients of faults occurring near voltage maximum are larger than those for faults occurring near voltage zero. It poses a problem for the ANN to make the right decision and this is so by virtue of the fact that the inputs of higher magnitudes swamp over those of lower magnitudes and hence selection of the useful characteristics in the latter are lost during the training process. However, as described before and again as shown in Figure 6-5, the low frequency transients of faults occurring near voltage zero are bigger in magnitude than those at voltage maximum. With a combined usage of both high- and low-frequency components, ANN can accurately differentiate between internal and external faults thereby overcome the aforementioned problem of fault inception angle, as evident by the results shown in Figure 6-17.

(a) 72km internal fault (b) external fault at sending end (c) external fault at receiving end

Figure 6-16 ANN outputs of AG faults (fault inception angle 90°)
6.4.2.3 Effect of Different Fault Types

Although most faults that occur in practice are single-phase to ground fault, it is important that the protection scheme should work well under different types of fault. Figure 6-18 shows that the proposed scheme can accurately respond to different fault types.

Figure 6-17 ANN outputs of BG faults
(a) internal fault at 72km from the sending end (inception angle 90°) (b) internal fault at 72km from the sending end (inception angle 0°) (c) external fault at the sending end (inception angle 90°) (d) external fault at the sending end (inception angle 0°)
6.4.2.4 Fault Close to Busbar

Here the scheme is also tested to see if it is suitable for distinguishing internal faults which are close to the busbars and are external faults. Figure 6-19 to Figure 6-22 show that the scheme can accurately detect internal and external faults which are located very close to the busbar at each end for AG, AB, ACG and ABCG fault respectively.

In Figure 6-20 (d), the fault decision can only be made when the output continues satisfying the threshold for 8 samples. This might cause a delay for the fault detection but can increase the reliability of the protection scheme to avoid errors.

Figure 6-18  ANN outputs of Faults at 72km (fault inception angle 90°)

(a) AB fault (b) ABG fault (c) ABCG fault
Figure 6-19 ANN outputs of AG faults (fault inception angle 90°)
(a) internal fault at 0km from sending end (b) external fault at the sending end (c) internal fault at 128km from the sending end (d) external fault at the receiving end

Figure 6-20 ANN outputs of AB phase faults (fault inception angle 90°)
(a) internal fault at 0km from sending end (b) external fault at the sending end (c) internal fault at 128km from sending end (d) external fault at the receiving end
Figure 6-21 ANN outputs of ACG faults
(a) internal fault at 0km from sending end (b) external fault at the sending end (c) internal fault at 128km from sending end (d) external fault at the receiving end

Figure 6-22 ANN outputs of ABCG faults
(a) internal fault at 0km from sending end (b) external fault at the sending end (c) internal fault at 128km from sending end (d) external fault at the receiving end
6.4.2.5 Effect of Source Capacity

The developed scheme is also tested when the sending end source capacity is increased from 5GVA to 35GVA. Figure 6-23 shows it can accurately differentiate between internal and external AG fault for this case, i.e. it is robust to change source capacities.

Figure 6-23 ANN outputs of AG faults for sending end source capacity of 35 GVA
(a) external fault at the sending end (fault inception angle 0°) (b) external fault at the sending end (fault inception angle 90°) (c) internal fault at 72km from the sending end (fault inception angle 0°) (d) internal fault at 72km from the sending end (fault inception angle 90°)

6.5 Summary

This chapter presents a new approach designed to classify fault types and differentiate internal and external faults using current data from one end only. The WT and ANN techniques are adopted to develop the scheme. The results show that the scheme demonstrates a high level of performance and its principal attributes are listed below:
• only one end current data is needed for the proposed scheme.
• the employed sampling rate of 16 kHz is sufficient for the techniques to display a high performance under a whole variety of different system and fault conditions.
• both high frequency and low frequency components are used to achieve high reliability and selectivity; this is particularly important since faults can occur both near voltage maximum and minimum.
• for both phase selection and fault detection scheme, same feature extraction stage is applied thereby improving the overall speed of the operation of the proposed scheme and making it easier to implement.

In the following chapters, the work is then extended to cater for systems having different parameters (e.g. Chinese 500kV EHV transmission line) and the effect of the penetration of the wind power generation is also considered.
Chapter 7  Current Based Phase Selection and Fault Detection Scheme Application and Case Studies on Chinese 500kV EHV Transmission Line

7.1  Introduction

A new phase selection and fault detection scheme using the combination of WT and ANN has been proposed and studied in the last chapter. It is shown that the scheme works well under various fault conditions for a typical UK 400kV transmission system. Since the project is a UK-CHINA joint funded project, it is also desirable to apply the designed scheme to a typical China 500kV transmission line. The robustness and accuracy of the scheme will be examined under this completely different transmission system in this chapter.

First of all, a typical China EHV (500kV) transmission line model is simulated in MATLAB Simulink. The simulation of the various faults under different fault types, fault inception angles, and fault locations is conducted based on the model, from which the fault currents are achieved. Then the feature extraction method is applied to the fault current signal. The results of the system simulation and the feature extraction from the new system are compared to that from the UK system.

After that, ANNs are trained using the data from the new system and are used to realize the phase selection and the fault detection. The ANNs are tested in different fault scenarios and the results are shown and discussed in the last part of this chapter.

7.2  System Model and Fault Simulation for the typical 500kV China transmission line

7.2.1  System Description

As depicted in Figure 7-1, the new system has similar architecture as the UK system. However, it is equipped with two traditional power sources with different source capacities. The source at the sending end, S1, has 1GVA capacity and that at the receiving end, S2, has 60 MVA capacity. 60 MVA is chosen for S2 as it is a typical
capacity of a wind farm. This allows S2 to be replaced with a wind farm for further studies in the next chapter.

On the S1 side, there is a short line of 10km connected to the S1; on the S2 side, this line is 30km. They are used to dictate the distances between the generators and the transmission line. The capacitor of the busbar is 0.1μF. The ground resistance is 2Ω and the fault resistance is 0.001Ω. The sampling time $T_s$ is $5 \times 10^{-5}$s therefore the sampling frequency is 20 kHz, compared to 16 kHz that is used in the 400kV UK power system. The sampling frequency of 20kHz is chosen as the modelling of the wind farm connection (e.g. DFIG that will be discussed later) is based on 20kHz in the MATLAB software.

This system is modelled using MATLAB Simulink Toolbox to facilitate the simulation of the wind farm which will be considered in the next chapter. It is shown in Figure 7-2 how the system looks like in the Simulink toolbox. It can be seen that the Simulink has a different user interface and different component models for the transmission system simulation compared to the EMTP.

![Figure 7-1 Schematic of the model for the China 500kV Transmission System](image)

![Figure 7-2 500kV China Power system model in MATLAB Simulink](image)
The length of the main transmission line is 300 km for the new system instead of 128km for the 400kV system. The parameters of the transmission line used are set up as shown in Table 7-1[65]. It should be noted that there are two transmission line blocks used in the system and the total length of them is always 300km, though the length of each individual line can be changed. Using this set-up, it is easier to change the fault location by simply altering the length of the two blocks.

**Table 7-1 Set-up for the transmission line block in Simulink [65]**

<table>
<thead>
<tr>
<th>Resistance (Ohms/km)</th>
<th>Positive Sequence</th>
<th>R1</th>
<th>0.0208</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Zero Sequence</td>
<td>R0</td>
<td>0.1148</td>
</tr>
<tr>
<td>Inductance (H/km)</td>
<td>Positive Sequence</td>
<td>L1</td>
<td>8.9840E-04</td>
</tr>
<tr>
<td></td>
<td>Zero Sequence</td>
<td>L0</td>
<td>2.2886E-03</td>
</tr>
<tr>
<td>Capacitance (F/km)</td>
<td>Positive Sequence</td>
<td>C1</td>
<td>1.2940E-08</td>
</tr>
<tr>
<td></td>
<td>Zero Sequence</td>
<td>C0</td>
<td>5.2000E-09</td>
</tr>
</tbody>
</table>

7.2.2 Simulation Results

As a baseline case, an AG fault at 32km is simulated and the current signal is shown in Figure 7-3. For comparison, the current signal from this fault situation for the previously studied UK 400 kV transmission system is also given in Figure 7-4. As shown in the two figures, the fault current waveforms are generally different between the two systems. This can be directly attributed to the significant change of the power system, e.g. voltage level, capacity of the source and the transmission line parameters, etc.

It can be seen that the amplitude of the current of the faulted phase (A) rapidly rises to several thousand amps after the fault occurrence point. It becomes much higher than that for the healthy phases (B and C). The feature is the same for both systems. Also, more fluctuations are seen in the current signal in the faulted phase (A) after the fault occurs in the new Chinese system. The feature extraction tools will be used to capture the frequency details for further comparison.
Figure 7-3 Fault Current Signal for the 32km AG fault of the China 500kV system, 90°

Figure 7-4 Fault Current Signal for the 32km AG fault of the UK 400kV system, 90°
7.3 Implementation of the Protection Scheme

7.3.1 Overview

The complete protection scheme has already been described in detail and demonstrated in the last chapter (also see Figure 6-2). In this chapter, although the transmission system is simulated via Simulink, the methods of using WT and ANN for realizing the protection scheme remain the same and the integrated toolboxes in MATLAB for both techniques are still used. However, new ANNs need to be trained by the extracted information from the new 500kV transmission system. Also the differences and similarities of the DWT results between the 500kV system and the 400kV system are investigated to understand and identify any potential issues the scheme may confront when it is applied to the new Chinese system.

7.3.2 Feature Extraction

The DWT is used to extract the frequency details. All settings and assumptions for its application are the same as before. The fault current signals are firstly decomposed into ten-level details. Then the accumulated energy of the ten level details is calculated for all three phases using eqn 6-1. The results from this will be taken as inputs for ANNs.

The results from the feature extraction are compared to the 400kV system. The effects of the different types of fault, different inception angles and different fault locations on the feature extraction results are also investigated.

All the distances that represent the locations for the fault, if not specified otherwise, are with reference to the distance between the fault location and the sending end.

7.3.2.1 Typical Case for Chinese 500kV System

Figure 7-5 shows the ten-level accumulated energy for an AG fault at 30km at 90° inception angle for the 500kV system. It can be seen that, the faulted phase (A) has significant higher energy magnitude compared to the healthy phases (B and C) except for D_6. The feature is generally similar with that for the UK 400kV system, although the spectral energy magnitudes are quite different.
7.3.2.2 Effect of the Fault Types

The accumulated energy for different fault types is also investigated. From Figure 7-6 to Figure 7-9, it was shown the energy of the ten-level details of WT decomposition for AG fault, AC fault, ACG fault and ABCG fault at 100km, respectively.

It can be seen in Figure 7-6, the faulted phase (A) shows significantly higher energy magnitude in both the HF and LF regimes compared to the healthy phases (B and C). The feature that distinguishes the healthy and the faulted phase(s) is the same as that for the 400kV system. Also as shown in Figure 7-7, both of the faulted phases (A and C) have very similar energy magnitude and are significantly higher than the healthy phase (B). In comparison, in Figure 7-8, when phase A and C are connected to the ground, the relation among the energy from the three phases is more complicated. For example, for D2, D3 and D5, the healthy phase (B) also has similar energy magnitude as phase A and C. When it comes to the three phase ground fault i.e. Figure 7-9, all three phases have very similar energy magnitudes in D6 to D10, but phase C has higher energy magnitude than phase A and B in D1 to D5.

Figure 7-5 Accumulated Energy of WT ten level details for the AG fault at 32km (90°) from the China 500kV system
Figure 7-6 Accumulated Energy of WT ten level details for the AG fault at 100km (90°) from the China 500kV system

Figure 7-7 Accumulated Energy of WT ten level details for the AC fault at 100km (90°) from the China 500kV system
Figure 7-8 Accumulated Energy of WT ten level details for the ACG fault at 100km from the China 500kV system

Figure 7-9 Accumulated Energy of WT ten level details for the ABCG fault at 100km from the China 500kV system
7.3.2.3 Effect of the Fault Inception Angle

The effect of different fault inception angles on the accumulated energy is also examined. For the AG fault at 20km, Figure 7-10 shows the ten-level WT energy details at both the 90° and 0° inception angle. As can be seen, the maximum energy level in the latter case is significantly lower than that in the former case for D1 to D5, but it is comparable for D6 to D10. In some cases, e.g. in D9 and D10, the accumulated energy for 0° is greater than that for the 90°. This feature is already seen in the 400kV system and it offers an opportunity to solve the data scaling problem aforementioned.

![Figure 7-10 Accumulated Energy of WT ten level details for the AG fault at 20km (90°and 0°) from the China 500kV system](image)

7.3.2.4 Effect of the Fault Locations

The effect of the fault locations is also examined and the CG fault at 90° inception angle is chosen for this study. It is shown from Figure 7-11 to Figure 7-14 when the faults happen at 20km, 60km, 180km and 280km respectively. It can be seen that, except D6, all the energy for the faulted phase C is dominating at all distances and it
appears that the distance does not have a major impact on this feature, although it does have an impact on the maximum energy magnitude.

Figure 7-11 Accumulated Energy of WT ten level details for the CG fault at 20km (90°) from the China 500kV system

Figure 7-12 Accumulated Energy of WT ten level details for the CG fault at 60km (90°) from the China 500kV system
Figure 7-13 Accumulated Energy of WT ten level details for the CG fault at 180km (90°) from the China 500kV system

Figure 7-14 Accumulated Energy of WT ten level details for the CG fault at 280km (90°) from the China 500kV system
7.3.3 ANN Architecture and Training

7.3.3.1 ANN for Phase Selection

For the phase selection scheme, as in the previous case of the UK 400 kV system, there is only one ANN used for all the fault types. There are 448 fault cases taken into account, which include ten types of faults, every 10km interval in terms of distances and two extreme fault inception angles (0° and 90°) for single-phase to ground fault and phase-to-phase fault. All the fault cases are taken as the data for ANN training, except the faults occurring at 50km, 150km and 270km, which are used for testing.

A new ANN is trained based on the data from the China 500kV system. It has a similar structure to the one used in the last chapter. It is a three-layered network which consists of 30 inputs in the input layer, 20 nodes in the hidden layer and 4 outputs in the output layer, like shown already in Figure 6-7. The details of the inputs and target outputs of the ANN are also shown below.

Inputs: 30 inputs which are the accumulated energy of ten-level details from WT decomposition of three phase current components.

Target outputs: 4 target outputs are defined and the examples are shown in the last chapter (Table 6-1). The same symbols are used in this chapter.

7.3.3.2 ANN for Fault Detection

Ten ANNs corresponding to ten types of fault are trained separately using different data from different types based on the new system. The topology of the ten ANNs is very similar to those used in the last chapter, as shown in Figure 6-10. Also, the node number of the hidden layer is varying from 18 to 22 depending on when the near optimal performance can be achieved. There are 30 inputs nodes and 1 output node for all the ANNs. The details of training data, inputs and target outputs of the ANN are shown below.

Training data: extracted feature from one fault type at different fault locations and fault angles
**Inputs:** 30 inputs which are the accumulated energy of ten-level details from WT decomposition of three phase current components for one type of fault

**Target outputs:** 1 target output is defined. ‘1’ represents the external fault; ‘10’ represents the internal fault; ‘0’ indicates no fault.

### 7.4 Results and Discussions

The results for the phase selection and the fault detection scheme are presented and discussed in this section.

#### 7.4.1 Phase Selection Results and Discussions

##### 7.4.1.1 Effect of Fault Location

The effect of the fault location on the phase selection scheme is firstly studied. Here the faults at 50km, 150km and 270 km are selected for testing, as shown in Figure 7-15 and Table 7-2. It can be seen from Figure 7-15 that when an ABG fault occurs at 50km, the outputs corresponding to A, B and G are “1” after the fault occurs while that for healthy phase C remains to be 0. Further, as shown in Table 7-2, the faults are precisely classified at all three distances that are tested. Like for the previous study based on the UK 400kV transmission system, this proves that the performance of phase selection scheme is not affected by the fault location.

![Figure 7-15 Phase Selection Results for the ABG fault at 50km from the China 500kV system](image-url)
Table 7-2 Results for Various Fault Locations (Fault inception angle: 90°)

<table>
<thead>
<tr>
<th>Fault locations</th>
<th>Fault types</th>
<th>Desired output</th>
<th>ANN output</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>A   B   C   G</td>
<td>A   B   C   G</td>
</tr>
<tr>
<td>50 km</td>
<td>CG</td>
<td>0   0   1   1</td>
<td>0.0000 0.0000 1.0000 1.0000</td>
</tr>
<tr>
<td></td>
<td>BC</td>
<td>0   1   1   0</td>
<td>0.0000 1.0000 1.0000 0.0000</td>
</tr>
<tr>
<td></td>
<td>BCG</td>
<td>0   1   1   1</td>
<td>0.0000 1.0000 1.0000 1.0000</td>
</tr>
<tr>
<td>150 km</td>
<td>CG</td>
<td>0   0   1   1</td>
<td>0.0000 0.0000 1.0000 1.0000</td>
</tr>
<tr>
<td></td>
<td>BC</td>
<td>0   1   1   0</td>
<td>0.0000 0.8923 0.9091 0.0000</td>
</tr>
<tr>
<td></td>
<td>BCG</td>
<td>0   1   1   1</td>
<td>0.0000 1.0000 1.0000 1.0000</td>
</tr>
<tr>
<td>270 km</td>
<td>CG</td>
<td>0   0   1   1</td>
<td>0.0000 0.0000 0.9657 0.9931</td>
</tr>
<tr>
<td></td>
<td>BC</td>
<td>0   1   1   0</td>
<td>0.0000 0.9995 1.0000 0.0000</td>
</tr>
<tr>
<td></td>
<td>BCG</td>
<td>0   1   1   1</td>
<td>0.0000 0.9742 0.9928 1.0000</td>
</tr>
</tbody>
</table>

7.4.1.2 Effect of Fault Inception Angle

Figure 7-16 and Figure 7-17 show the results for the AC fault at 50km occurring at 90° and 0° inception angle, respectively. The results correctly reflect the faulted phases (A and C) and the healthy phase (B). For more test cases under those two extreme conditions, the results are shown in Table 7-3. It shows that phase selection scheme works well in all the extreme cases simulated here. This means that by making use of both the HF and LF information from the feature extraction stage, the data scaling issue resulting from the different fault inception angles of the faults is appropriately managed.
Figure 7-16 Phase Selection Results for the AC fault at 50km (90°) from the China 500kV system

Figure 7-17 Phase Selection Results for the AC fault at 50km (0°) from the China 500kV system
### Table 7-3 Results for various fault inception angles (Fault location: 150km)

<table>
<thead>
<tr>
<th>Fault inception angle</th>
<th>Fault types</th>
<th>Desired output</th>
<th>ANN Actual output</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>A   B   C   G</td>
<td>A    B    C    G</td>
</tr>
<tr>
<td>0°</td>
<td>AG</td>
<td>1   0   0   1</td>
<td>0.9892 0.0001 0.0000 0.9803</td>
</tr>
<tr>
<td></td>
<td>AB</td>
<td>1   1   0   0</td>
<td>1.0000 1.0000 0.0000 0.0139</td>
</tr>
<tr>
<td></td>
<td>BG</td>
<td>0   1   0   1</td>
<td>0.0000 0.9906 0.0000 0.9996</td>
</tr>
<tr>
<td></td>
<td>BC</td>
<td>0   1   1   0</td>
<td>0.0000 0.9992 0.9983 0.0000</td>
</tr>
<tr>
<td></td>
<td>CG</td>
<td>0   0   1   1</td>
<td>0.0000 0.0000 0.9953 0.9999</td>
</tr>
<tr>
<td></td>
<td>AC</td>
<td>1   0   1   0</td>
<td>0.9999 0.0000 0.9999 0.0038</td>
</tr>
<tr>
<td>90°</td>
<td>AG</td>
<td>1   0   0   1</td>
<td>1.0000 0.0000 0.0000 1.0000</td>
</tr>
<tr>
<td></td>
<td>AB</td>
<td>1   1   0   0</td>
<td>1.0000 0.9999 0.0000 0.0000</td>
</tr>
<tr>
<td></td>
<td>BG</td>
<td>0   1   0   1</td>
<td>0.0000 0.9529 0.0000 0.9984</td>
</tr>
<tr>
<td></td>
<td>BC</td>
<td>0   1   1   0</td>
<td>0.0000 0.8923 0.9091 0.0000</td>
</tr>
<tr>
<td></td>
<td>CG</td>
<td>0   0   1   1</td>
<td>0.0000 0.0000 1.0000 1.0000</td>
</tr>
<tr>
<td></td>
<td>AC</td>
<td>1   0   1   0</td>
<td>0.9914 0.0000 0.9983 0.0000</td>
</tr>
</tbody>
</table>

#### 7.4.1.3 Effect of Different Fault Types

From Figure 7-18 to Figure 7-20, it is shown respectively how the protection scheme works under three different fault types - BCG, BC (90°) and BG (90°). For example, in Figure 7-18, when the BCG fault happened, the output for the B, C and G becomes
one after the fault occurring point. Furthermore, as shown in Figure 7-19 and Figure 7-20, the BC and BG fault are also correctly selected.

The phase selection results for ten types of faults are summarized in Table 7-4. It can be seen that the faulted phase(s) and the healthy phase(s) are all correctly identified in the cases considered. It can be concluded that the phase selection scheme works very accurately for different types of fault.

**Figure 7-18 Phase Selection Results for the BCG fault at 50km from the China 500kV system**
Figure 7-19 Phase Selection Results for the BC fault at 50km 90° from the China 500kV system

Figure 7-20 Phase Selection Results for the BG fault at 50km 90° from the China 500kV system
Table 7-4 Results for various fault types
(Fault inception angle: 0° and fault location: 270km)

<table>
<thead>
<tr>
<th>Fault types</th>
<th>Desired output</th>
<th>ANN output</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>AG</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>BG</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>CG</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>AB</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>AC</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>BC</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>ABG</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>ACG</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>BCG</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>ABCG</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

7.4.2 Fault Detection Results and Discussions

The same threshold criteria as outlined in chapter 7 are also used herein to help refine the fault detection results, i.e.

- if the output is less 0.5, then reset output to be 0, indicating non-fault;
- if the output is greater than 0.5 but less than 5.5, then reset output to be 1, indicating external fault;
- if the output is greater than 5.5, then reset output to be 10, indicating internal fault;
Also if the ANN output continuously satisfied the second or the third optimal threshold for 8 samples, then it will be identified as an external or an internal fault. The detailed results are discussed in the following sections.

### 7.4.2.1 Typical Response to Internal and External Faults

In Figure 7-21 (a), (b) and (c) show the ANN output for the internal fault at 145km from the sending end, the external fault at the sending end and the external fault at the receiving end respectively. In the plots, The ANN outputs are 10, 1 and 1 respectively when the fault occurs. Also, it can be seen that, compared to the internal fault, the output for the external fault at the receiving or sending end has more fluctuations. Apparently, the threshold method helps to overcome the uncertainties due to the fluctuations in the external fault case.

![Figure 7-21](image)

**Figure 7-21 ANN outputs of AG faults (fault inception angle 90°)**

(a) 145km internal fault (b) external fault at sending end (c) external fault at receiving end

132
7.4.2.2 Effect of Inception Angle

Figure 7-22, Figure 7-23 and Figure 7-24 show how the fault detection scheme works at two extreme inception angles for the internal AG fault at 275km, the external fault at the sending end and the external fault at the receiving end respectively. Again the external fault shows more fluctuations near the fault occurrence point, although the internal and external faults are detected correctly. This means that the problem of the data difference between the extreme inception angles is again well handled by the combined use of the HF and LF information from the feature extraction data.

![Graph showing ANN outputs of AG faults at 275km - internal fault]

Figure 7-22 ANN outputs of AG faults at 275km - internal fault

(a) 90° (b) 0°
Figure 7-23 ANN outputs of AG faults at the sending end – external fault

(a) 90° (b) 0°

Figure 7-24 ANN outputs of AG faults at the receiving end – external fault

(a) 90° (b) 0°
7.4.2.3 Effect of Different Fault Types

Figure 7-25 and Figure 7-26 present the ANN outputs of the fault detection scheme for different fault types for the internal fault (at 145km) and the external fault at the sending end respectively. The fault types shown here include AG, AB, ACG, ABCG. From Figure 7-25, it can be seen that there is little difference between the data without threshold method and that with the threshold method and they are all correctly identified as the internal fault. Also, as shown in Figure 7-26, even though there are some fluctuations especially for the type AG and AB faults, all the data are close to 1, which clearly signifies external faults.

![ANN outputs of faults at 145km – internal fault](image)

(a) AG (b) AB (c) ACG (d) ABCG
As discussed in the last chapter, the faults occurring close to busbar are the most difficult cases to detect; hence they are also tested here. From Figure 7-27 to Figure 7-29, the fault detection results for the AG, ACG and ABCG faults are shown respectively. Figure 7-27 (a) and (c) are the results for the internal faults at 0km and 300km and the output becomes 10 after the fault inception point which indicates internal faults. In contrast, Figure 7-27 (b) and (d) are the results for the external fault at the sending end and the receiving end and the results are 1 which signify external faults. Figure 7-28 and Figure 7-29 are very similar to Figure 7-27.

Overall, the results and analysis discussed above have clearly shown that the scheme can accurately distinguish between internal and external faults which are located very close to the busbar at each end.
Figure 7-27 ANN outputs of the AG fault close to busbar

(a) 0km 90° (b) sending end 90° (c) 300km 90° (d) receiving end 90°

Figure 7-28 ANN outputs of ACG faults close to busbar

(a) 0km (b) sending end (c) 300km (d) receiving end
7.5 Summary

In this chapter, the newly developed protection scheme is applied to a typical China 500kV transmission system. Both the phase selection and the fault detection schemes are verified for this system under different fault situations. The results show that although the power system has changed significantly in terms of system parameters (e.g. the line length, source capacity etc.) which result in different fault current signals and different fault transients, the scheme still works accurately and reliably for the new system. The main reason is that the extracted features that are used to realize the protection scheme are not influenced by the changes of the system, although the fault currents and the fault transients are different under the new system conditions.

It should be noted that two principal changes made to the ANN to realize the schemes for the new system are:

- For the phase selection, an ANN with the similar structure as the last chapter (one hidden layer with 20 nodes) is trained using the new data.
• For the fault detection, ten ANNs with the similar structures as the last chapter are trained using the new data. The changes include changing the number of nodes in the hidden layer to achieve the near optimal performance.

The next chapter will be looking at the impact of the wind farm on the protection scheme.
Chapter 8  Current Based Phase Selection and Fault Detection Scheme Application and Case Studies on Chinese 500kV EHV Transmission Line with Both Traditional Generation and Wind Generation

8.1 Introduction

The performance of novel phase selection and fault detection scheme developed have been well demonstrated for both the UK 400kV EHV transmission system (chapter 7) and the China 500kV EHV transmission system (chapter 8).

Since renewable resources become increasingly important nowadays, many of the transmission systems have the penetration of renewable generation resources such as wind farms, solar power plants and bioenergy farms, etc. In this context, their effects on the transmission system as well as the power protection scheme applied to the system also become crucial and therefore need to be investigated. The wind power will be the focus of the study herein.

This chapter starts with an introduction to wind power, followed by a comparison of the fault simulation results between the system without and with a wind farm based on the typical China 500kV transmission system model as described in the last chapter. Then the phase selection and fault detection schemes are applied to the system with the wind farm connection. Again the DWT and ANN are utilized in the scheme to realize feature extraction and decision making, respectively. The results are shown and discussed in details in the final part of this chapter.

8.1.1 Wind Power

The human being has been utilizing wind power for more than 3000 years. However, before the twentieth century, it was mainly used for providing mechanical power for applications such as grinding grain, pumping water, etc. Nowadays, wind farm is more and more being used as a renewable power resource for replacing the traditional fossil fuel fired power plant[66].
The most common device that is utilized to turn wind power into electricity is called wind turbine (Figure 8-1). It was invented at the beginning of the twentieth century. The technology was greatly improved since early 1970s due to the requirement for sustainable energy resources. Wind energy was identified as one of the most important clean energy resources. In the past years, the wind power capacity was dramatically increased year by year. Figure 8-1 shows a wind farm in Germany. Figure 8-2 shows the worldwide wind power capacity in 2012 [67].

It can be seen that by the end of 2012, China has the most wind power capacity in the world. The USA and Germany are ranked 2nd and 3rd respectively. Since the wind power becomes more and more critical, it makes practical sense to study the effect of wind power on the power system and the protection scheme, when it is connected to power systems.

Figure 8-1 Wind Turbine Farms in Germany

Figure 8-2 Worldwide Wind Power Capacity in 2012 [67]
8.1.2 Possible Impact

On one hand, the amount of wind power generation contributes only a small portion of the overall power generation as of now. On the other hand, its capacity keeps increasing. It has also already started to replace the output of conventional power plants. The expanding penetration of the wind generation into the power grid started to influence the behaviour of the power system. In order to identify possible problems that may be caused by this change, the relevant study needs to be carried out and the mitigation measure for the problems can then also be considered[66].

The generators are the fundamental parts of a power system and they determine the dynamic behaviour of the system. In the past, the power is mostly generated with the direct grid-coupled synchronous generators. It has been studied for years how these conventional generators behave under various system conditions, hence, their characteristics are well known. However, the generator for wind turbine is changed to those that are grid-coupled via power electronic converters or squirrel cage induction generators. The new types of generator interact differently with the power system, compared to conventional generators. Furthermore, the interaction with the power system between the various types of wind turbines presently applied is also different, therefore, they must be treated separately [66].

In summary, the study here is to find if wind turbines have an impact on the transients caused by a fault and also if it might affect the performance of the designed protection scheme.

8.1.3 Different Types of Wind Turbines

There are various types of wind turbine in the market today. They can be grouped into two main categories: [66]

- Fixed Speed Wind Turbines
- Variable Speed Wind Turbines

Double Fed Induction Generator (DFIG) is one of the variable speed wind turbines and is the most commonly used wind turbine nowadays and hence this is the one studied in this work.
Figure 8-3 DFIG topologies [66]

Figure 8-3 shows the topology of the DFIG system. Different from other types of generators used for wind turbines, DFIG systems are capable of maintaining the amplitude and frequency of their output voltages at a constant value, which is not affected by the speed of the wind. This allows DFIGs to be directly connected to the AC power network and they can be easily synchronized with the network[66].

8.2 System Model and Fault Simulation

8.2.1 System with wind farm penetration

MATLAB Simulink has an integrated DFIG model and this can be directly added into the 500 kV transmission line model built in the previous chapter, so that the effect of wind turbine on the fault transients can be simulated. Based on the China 500kV model in Chapter 8, the power source of the receiving end (S2) is replaced by a 60MVA wind farm in this chapter, as shown in Figure 8-4. The wind farm comprises 40x1.5MVA wind turbines (using DFIG) in parallel. Two ideal transformers are used so that the voltage level of the wind farm can be firstly increased from 575V to 25kV on the short 30 km line and then be further increased to 500kV on the main transmission line.
8.2.2 Simulation Results

The effect of the penetration of wind power on the faulted current signals is firstly investigated. Figure 8-5 shows both the fault current signals from the system with and without wind power. Figure 8-5(a) represents the signal from the system with wind power and Figure 8-5(b) represents that from the system without wind power. It is an AG fault occurring at 20km from the sending end at the maximum fault inception angle (90°). It can be seen that from the fault occurrence point on, the current signal for the faulted phase (A) in these two situations are very similar. This is as expected as the location of the fault occurrence point is far away from the wind farm. It can also be seen that for the signal of the healthy phases, there is relatively large difference particularly in terms of phase angles despite amplitudes being similar. Similar trends are found for other types of fault, though they are not shown here.

In contrast, Figure 8-6 shows the signal comparison when the fault occurs close to the wind farm. It can be seen that the fault current signal does differ both in terms of the magnitudes and the wave shapes. This is as a direct consequence of the difference between the characteristics of wind power source and the traditional power source. However, it should be noted that, in general, the difference of the amplitudes of the current waves between those two situations is small even when the fault occurrence point is almost at the receiving end. This can be attributed to the fact that the wind farm only contributes to less than 6% in terms of the overall power capacity, i.e. the traditional power source is still dominating in the transmission system.

The next step is to investigate what is the impact of the wind turbines on the fault transients by employing the feature extraction technique.
Figure 8-5 Fault Current signals in the system for an AG fault at 20km, 90°

(a) with wind farm  (b) without wind farm
Figure 8-6 Fault Current signals in the system for an AG fault at 280km, 90°

(a) with wind farm  (b) without wind farm
8.3 Implementation of the Protection Scheme

The procedure to realize the protection scheme is the same as that described in the last chapters (section 7.3.1 and 8.3.1); therefore it will not be repeated here.

8.3.1 Feature Extraction

As described before, ten levels of frequency details are selected to support the protection scheme. Then, the accumulated energy of each detail is calculated and used as the input for decision making. The results of the 500kV system with traditional power source and with wind farm will also be compared.

If not specified otherwise, in all cases the solid line with results presented represents results from the model with the wind farm and the dashed line represents that from the model without the wind farm.

8.3.1.1 Effect of the Fault Locations

The effects of the fault location on the feature extraction results are shown here. The details from the feature extraction for the phase A of AG fault occurring at 0km, 180km and 270km are shown in Figure 8-7, Figure 8-8 and Figure 8-9 respectively. It can be seen that when the fault occurs at 0km from the sending end, there is little difference between the accumulated energy between the case with wind farm and that without wind farm. As the distance from the sending end increases (e.g. in Figure 8-8 and Figure 8-9), the difference between the two cases becomes larger. In those cases, it is found that from $D_6$ to $D_{10}$ (Lower-Frequency information), the energy is slightly lower for the system without wind farm than that with the wind farm, whereas no regular pattern can be found for $D_1$ to $D_5$ (Higher-Frequency information).

It can also be seen from the three figures, that the magnitude of the accumulated energy varies considerably with the change of the fault location regardless of whether there is a wind farm connected or not.

Figure 8-10 shows the ten-level accumulated energy details of the AG fault at 270km for the system with the wind farm. It is apparent that the faulted phase (A) has
significantly higher energy compared to that for the healthy phases (B and C) except D₆.

Figure 8-7 Accumulated Energy of WT ten level details for the AG fault at 0km (90°), only for phase A

Figure 8-8 Accumulated Energy of WT ten level details for the AG fault at 180km (90°), only for phase A
Figure 8-9 Accumulated Energy of WT ten level details for the AG fault at 270km (90°), only for phase A

Figure 8-10 Accumulated Energy of WT ten level details for the AG fault at 270km (90°), with the wind farm
8.3.1.2 Effect of Fault inception Angle

The effect of the fault inception angle on the accumulated energy is studied and the case where the fault occurs in the middle (160km from the sending end) is selected. Figure 8-11 and Figure 8-12 show the results for the phase A for the AG fault occurring at $90^\circ$ and $0^\circ$ respectively. It can be seen that for both cases, the wind farm has an impact on the accumulated energy; for the $0^\circ$ case (Figure 8-12), the difference is bigger, which can be clearly seen from $D_1$ to $D_5$.

It can also be found that from $D_1$ to $D_5$, the maximum accumulated energy is significantly lower for the $0^\circ$ case than that for the $90^\circ$ case for both scenarios. From $D_6$ to $D_{10}$, it is comparable for the two extreme angles. The feature is also little influenced by the penetration of the wind farm and can therefore still be utilized.

![Figure 8-11 Accumulated Energy of WT ten level details for the AG fault at 160km (90°), only for phase A](image)
Figure 8-12 Accumulated Energy of WT ten level details for the AG fault at 160km (0°), only for phase A

8.3.1.3 Effect of Fault Types

The fault AB, ACG and ABCG are shown respectively in Figure 8-13, Figure 8-14 and Figure 8-15. It can be seen in Figure 8-13 that the faulted phases (A and B) have higher energy than the healthy phase (C) in all ten levels. For the type ACG fault in Figure 8-14, there is an anomaly showing up in D6, where the energy for the healthy phase (B) is quite comparable to phases A and C. For the ABCG case in Figure 8-15, all the energy values for the three phases in all the levels are very comparable.
Figure 8-13 Accumulated Energy of WT ten level details for the AB fault at 160km (90°)

Figure 8-14 Accumulated Energy of WT ten level details for the ACG fault at 160km
8.3.2 ANN Architecture and Training

It has already been discussed in detail in the previous chapters as how ANNs work, how ANNs are trained and how to use them to realize the decision making for the protection scheme. Only the final trained ANNs are briefly discussed here.

8.3.2.1 ANN for Phase Selection

An ANN with 30 nodes in the input layer, 20 nodes in the hidden layer and 4 nodes in the output layer, is trained for phase selection using the data from the 500kV system with wind farm. Again 448 fault cases are taken into account. The cases comprise ten types of faults, every 10km interval in terms of distances and two extreme fault inception angles (0° and 90°) for single-phase to ground fault and phase-to-phase fault. All the fault cases except for those the faults occurring at 50km, 150km and 270km (which are used for testing), are used for ANN training.
8.3.2.2 ANN for Fault Detection

Ten ANNs for fault detection, similar to what are used in the last chapter are trained using the data from the new system. The optimal number of nodes in the hidden layer is identified by trial and error. It varies from 18 to 22.

8.4 Results and Discussions

The performance of phase selection and fault detection schemes is studied and the results are shown in this section for a system when the wind farm is connected into the China typical 500kV transmission line.

The numbers that represent the fault locations, if not specified otherwise, mean the distance of the fault from the sending end of the power system.

8.4.1 Phase Selection Results

The phase selection is again taken as the first step to realize the power protection scheme. Different fault locations, different fault inception angles and different fault types are taken into account.

The output of the faulted phase is expected to be ‘1’ after the fault occurrence point. If it is a fault connected to the ground, then the output for the ground should also be ‘1’ after the fault happens. The healthy phase should remain 0.

8.4.1.1 Effect of Fault Location

An ACG fault at 50km is selected and the result is shown in Figure 8-16. It can be seen that the actual outputs for phase A, phase C and G become 1 when the fault occurs. More tests at three distances (50km, 150km, and 270km) are done and the results are shown Table 8-1. The results show that the phase selection scheme classifies the fault accurately for different fault locations. It is immune to fault location.

Although there are differences that have been identified at the feature extraction stage due to the penetration of the wind farm, there is hardly any impact on the accuracy of the phase selection as shown by the results.
Figure 8-16 Phase Selection Results for the ACG fault at 50km

Table 8-1 Results for Various Fault Locations (Fault Inception angle: 90°)

<table>
<thead>
<tr>
<th>Fault locations</th>
<th>Fault types</th>
<th>Desired output</th>
<th>ANN output</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>A   B   C   G</td>
<td>A   B   C   G</td>
</tr>
<tr>
<td>50 km</td>
<td>CG</td>
<td>0    0   1   1</td>
<td>0.0000   0.0000   1.0000   1.0000</td>
</tr>
<tr>
<td></td>
<td>BC</td>
<td>0    1   1   0</td>
<td>0.2733   1.0000   0.9999   0.0064</td>
</tr>
<tr>
<td></td>
<td>BCG</td>
<td>0    1   1   1</td>
<td>0.0000   0.9919   1.0000   0.9401</td>
</tr>
<tr>
<td>150 km</td>
<td>CG</td>
<td>0    0   1   1</td>
<td>0.0000   0.0000   1.0000   1.0000</td>
</tr>
<tr>
<td></td>
<td>BC</td>
<td>0    1   1   0</td>
<td>0.0000   1.0000   0.9913   0.0000</td>
</tr>
<tr>
<td></td>
<td>BCG</td>
<td>0    1   1   1</td>
<td>0.0000   0.9999   1.0000   0.9746</td>
</tr>
<tr>
<td>270km</td>
<td>CG</td>
<td>0    0   1   1</td>
<td>0.0000   0.0000   0.9761   1.0000</td>
</tr>
<tr>
<td></td>
<td>BC</td>
<td>0    1   1   0</td>
<td>0.0093   1.0000   0.8487   0.0000</td>
</tr>
<tr>
<td></td>
<td>BCG</td>
<td>0    1   1   1</td>
<td>0.1076   0.9367   1.0000   1.0000</td>
</tr>
</tbody>
</table>
8.4.1.2 Effect of Fault Inception Angle

CG faults at 150km are taken as examples to show the actual ANN outputs. The results for the faults at phase angle 90° and 0° are shown in Figure 8-17 and Figure 8-18 respectively. Further, a series of tests are also done for these two extreme fault inception angles and the results are shown in Table 8-2. It can be seen that the scheme can identify the faults correctly at the extreme inception angles for the system with the wind farm.

Figure 8-17 Phase Selection Results for the CG Fault at 150km (90°)

Figure 8-18 Phase Selection Results for the CG Fault at 150km (0°)
Table 8-2 Results for Various Fault Inception Angle (Fault Location: 150km)

<table>
<thead>
<tr>
<th>Fault Inception Angle</th>
<th>Fault Types</th>
<th>Desired output</th>
<th>ANN Actual output</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>0°</td>
<td>AG</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>AB</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>BG</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>BC</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>CG</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>AC</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>90°</td>
<td>AG</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>AB</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>BG</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>BC</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>CG</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>AC</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>

8.4.1.3 Effect of Different Fault Types

The variations of the outputs with time for different fault types (AG and BCG) are shown in Figure 8-19 and Figure 8-20 respectively. Also the phase selection results for all ten types of faults occurring at 270km are shown in Table 8-3 and they prove
that the phase selection scheme is immune to different fault types for the system with the wind farm connection.

Figure 8-19 Phase Selection Results for the AG Fault at 50km (90°)

Figure 8-20 Phase Selection Results for the BCG Fault at 50km
8.4.2 Fault Detection Results

The threshold criteria discussed in section 7.4.2 is also used here to achieve more accurate and stable results for the fault detection scheme.

8.4.2.1 Typical Response to Internal and External Fault

Figure 8-21 shows some typical responses for the internal fault at 150km, the external fault at the sending end and the external fault at the receiving end respectively for the AB fault at an inception angle of 90°. In Figure 8-21 (a), the
ANN output becomes 10 after the fault occurring point clearly signifying an internal fault. In Figure 8-21 (b) and (c), even though with some fluctuations being present, the output becomes stable on the value of 1, which identifies an external fault.

![Figure 8-21 ANN Outputs of AB Faults (Fault Inception Angle 90°)](image)

Figure 8-21 ANN Outputs of AB Faults (Fault Inception Angle 90°) (a) 150km internal fault (b) external fault at sending end (c) external fault at receiving end

### 8.4.2.2 Effect of Different Fault Inception Angles

Figure 8-22 and Figure 8-23 show the actual outputs of the fault detection for the AG fault occurring at the maximum inception angle and that at the minimum inception angle respectively. In both figures, the subplots correspond respectively to the internal fault at 150km (a), the external fault at the sending end (b) and the external fault at the receiving end (c). It can be seen that although both the internal and external faults are identified correctly, the outputs relating to the internal faults reach a near steady-state level whereas it tends to somewhat fluctuate for the external faults.

Overall the scheme performs very well for the two extreme inception angle cases.
Figure 8-22 ANN Outputs of the AG Fault (Fault Inception Angle 90°) (a) 150km internal fault (b) external fault at sending end (c) external fault at receiving end

Figure 8-23 ANN Outputs of AG Fault (Fault Inception Angle 0°) (a) 150km internal fault (b) external fault at sending end (c) external fault at receiving end
8.4.2.3 Effect of Different Fault Types

The effect of different fault types on the fault detection scheme is also examined and shown in Figure 8-24, Figure 8-25, and Figure 8-26. They correspond to the internal fault at 150km, the external fault at the sending end, and the external fault at the receiving end respectively. For each fault scenario, the fault type AG, AB, ACG and ABCG are tested respectively as shown in the subplots. The ANN outputs for internal faults are 10 in Figure 8-24 and the outputs are 1 for external faults in both Figure 8-25 and Figure 8-26 after the fault inception point, which clearly shows that the fault detection scheme is suitable for different fault types.

Figure 8-24 ANN Outputs of the Internal Faults at 150km (a) AG (90°) (b) AB (90°) (c) ACG (d) ABCG
Figure 8-25 ANN Outputs of the External Faults at Sending End (a) AG (90°) (b) AB (90°) (c) ACG (d) ABCG

Figure 8-26 ANN Outputs of the External Faults at the Receiving End (a) AG (90°) (b) AB (90°) (c) ACG (d) ABCG
8.4.2.4 Effect of different internal fault locations

Also, the effect of the different internal fault locations on the fault detection scheme is investigated. As shown in Figure 8-27, the fault locations at 40km, 150km, 260km are selected. All outputs show that the internal faults are correctly detected. This means that even though the wind farm does have an increasing impact on the simulation and feature extraction results while the fault location approaches the wind farm, it has little influence on the results of the fault detection scheme.

![Figure 8-27 ANN Outputs of AG Internal Faults (Fault Inception Angle 90°) (a) 40km (b) 150km (c) 260km](image)

8.4.2.5 Fault Close to Busbar

Finally, the protection scheme is tested on the faults occurring closed to the busbars. The fault detection results for the AG and ABCG faults are shown in Figure 8-28 and Figure 8-29 respectively. For subplots (a) and (c) in both figures, the outputs become 10 after the fault inception point which indicates internal faults. For subplots (b) and (d) in both figures, the output is 1 which signifies an external fault.
Figure 8-28  ANN Outputs of the AG Fault Close to Busbar (a) 0km 90° (b) sending end 90° (c) 300km 90° (d) receiving end 90°

Figure 8-29  ANN Outputs of the ABCG Fault Close to Busbar (a) 0km (b) sending end (c) 300km (d) receiving end

165
8.5 Summary

The proposed power system protection scheme is applied to a typical China 500kV transmission system with a wind farm in this chapter. The fault current signals from the new system with the wind farm are firstly compared to that from the system without the wind farm. It is found that as the fault location gets closer to the wind farm, more differences in the waveforms are observed. Then the outcome from the feature extraction stage is also investigated and compared. Here it is seen that the differences between the accumulated energy of the fault transients in the two scenarios become lager when the fault location is closer to the wind farm. Also for the LF (D_6 to D_{10}) features, the energy from the case without wind farm is generally lower, whereas for the HF (D_1 to D_5) features, no regular pattern can be identified in the cases studied. The fault inception angle also has an impact on the outcomes, e.g., at 0°, the HF (D_1 to D_5) features are more sensitive to the penetration of the wind farm, compared to that for 90°.

Despite the differences found in the fault currents and fault transients, the main features that are utilized to realize the protection scheme is not affected by the penetration of the wind farm and the results for both phase selection and fault detection schemes are found to be satisfactory in the test cases studied.

It thus proves that the scheme proposed in this work is accurate and robust under different system and fault conditions, and more importantly, it is capable of handling the penetration of the wind farm.
Chapter 9  Conclusions and Outlook

9.1  Introduction

In this chapter, the major findings and achievements of the research project are reviewed; some possible future work for further enhancing the novel phase selection and fault detection scheme proposed in this thesis are described.

9.2  Review of Major Findings and Achievements

In the context of the fast expanding power system with increasing penetrations of renewable resource, a novel power protection scheme based on WT and ANN is proposed and demonstrated in this work.

The background on challenges of traditional power protection schemes is introduced. The opportunity of developing a new scheme is analysed and the features that the scheme should have are summarized.

The definition of fault, the types of fault and its influences are described. The basic principle of power protection scheme as well as the relevant techniques is introduced, for example, EMTP, WT, and ANN.

The former studies on the TBP scheme are reviewed and summarized. It is explained in detail the content of this work in relation to the new power protection scheme developed herein.

The simulation of the typical UK 400kV transmission line based on EMTP is done. The results of the fault current signal under different fault conditions from the model are shown, analysed and compared. It was found that the fault transients are not visible in the fault current signals principally due to the magnitudes of such signals are relatively much smaller than the power frequency components. Signal analysing tool is thus required to extract the important information relating to the fault transients. Also, it is shown that the waveforms of the fault transients are dependent on the fault types, the fault inception angles and the fault locations.
The reason as to why the WT is used for feature extraction is introduced, together with the associating methodology. The WT technique is demonstrated in detail with examples. The Db4 mother wavelet is chosen as an optimal option considering both the accuracy and the speed. The four-level decomposition results for the fault current signals under different fault conditions are shown and compared. The main findings can be summarized as shown below:

1) The WT can extract the feature of the fault transients in both the frequency and time domain from the fault current signal.
2) The spectral energy of the wavelet coefficients needs to be used instead of the coefficients themselves.
3) With the application of the WT decomposition and the calculation of the spectral energy, the feature that differentiates the faulted phase(s) and healthy phase(s) is more outstanding.

Artificial intelligence techniques are introduced in detail, with a focus on the FL and the ANN. Why and how they are used is also discussed. The decision making intermediate step based on FL and ANN to realize the phase selection is then tested. The results show that though the phase selection can be well achieved, the scheme that only utilizes a limited high frequency part of the WT results, requires certain fault information beforehand. As a result, it is not applicable in reality. This technique needs further improvements.

The phase selection scheme based on the fault current signals using WT and ANN is introduced and demonstrated. Based on the model described, wavelet toolbox is applied to decompose fault current signals for feature extraction. Ten-level WT decomposition is performed instead of four-level and also both the HF and LF energy information from the feature extraction stage are taken as inputs into an ANN to conquer the problems aforementioned. The detailed construction of ANN is also introduced. The phase selection results are then shown and discussed.

As the second part of the protection scheme, the fault detection scheme is also demonstrated. The feature extraction stage as well as the training and testing of
ANNs for fault detection are also explained. Finally, the results are shown and analysed.

The results show that the scheme researched and developed is capable of realizing the phase selection and fault detection accurately and efficiently under different fault conditions for the typical UK 400kV EHV system. This is followed by modelling a typical 500 kV China transmission system and the various types of fault are simulated to provide data to examine the performance of the protection scheme developed as part of the research.

The results show that, even in a significantly different transmission system, the scheme can still work accurately and efficiently to fulfil the function of the phase selection and the fault detection.

The modelling of the China 500kV transmission system with a wind farm is conducted. Compared to the Chinese system, the traditional power source at the receiving end of the power system is replaced by a wind farm. The protection scheme is again applied to the system.

The simulation and feature extraction results show that, with the wind farm, there are increasing differences in the fault transients compared to that for the traditional source, as the location of the fault approaches the wind farm. However, the results for the scheme show that it is robust well despite of such system changes.

**Contribution**

In summary, the attributes of the novel power protection scheme proposed in the work are as follows:

- only the current data from one end of the transmission line is required for the proposed scheme.
- the current signal sampling rate of 16 kHz (for the UK 400kV transmission system) and 20 kHz (for the China 500kV transmission system) are sufficient for the techniques to display a high performance under a whole variety of different system and fault conditions. The sampling rate is
considerably lower than other TBP schemes, thus it has much lower requirement for the microprocessor.

- both high frequency and low frequency components are used to achieve high reliability and selectivity; this is particularly important since faults can occur both near voltage maximum and minimum.
- for both phase selection and fault detection scheme, same feature extraction stage is applied thereby improving the overall speed of operation of the proposed scheme and making it easier to implement.
- for a completely different power system and the penetration of the wind farm, the scheme can be easily adjusted to fulfil the protection requirements, by simply training new ANNs (with similar structure) for both the phase selection and fault detection using the new data set from the new system.

In general, the scheme proposed in this work gives a high performance EHV protection scheme that can achieve the phase selection and the fault detection accurately and reliably under different fault conditions for different power systems.

9.3 Future Work

The power protection scheme proposed in this work is already validated against the typical UK 400kV and China 500kV EHV power transmission system. Also, the effect of the penetration of a wind farm on the scheme is studied. However, for real-life applications of the scheme, more practical work needs to be carried out. Also, depending on the requirement of the specific system, new ANNs need to be trained separately and the fault data need to be made available for the feature extraction.

It is proposed here that more realistic power system conditions (in particular practical data) can be studied and used to test the power protection scheme and the hardware for realizing the scheme in real transmission systems should be designed in the future. A few possible directions are listed here:

- to simulate a system with a large penetration of wind farm

In this work, the Chinese transmission system contains a 60MVA wind farm and a 1GVA of the traditional power source. In future, with the rapid development of
the wind power, it is worthwhile to check if the protection scheme still works with an EHV transmission system connected with a large penetration of wind farm. Also, a more complex system topology with more penetrations of wind farms should be considered.

- In this work, a constant speed of wind is used. In future, the nature of wind (variation of speeds) needs to be considered.
- Other renewable resource penetrations into the system, such as solar power plants, bioenergy farms, etc. need to be considered.
- Design and test the hardware that can realize the scheme in reality.
Literatures


Appendix A

It is shown here the additional fault current waveforms for chapter 4.

Figure A-1 Fault current waveforms for BG fault, 32km, 90°

Figure A-2 Fault current waveforms for CG fault, 32km, 90°
Figure A-3 Fault current waveforms for BC fault, 32km, 90°

Figure A-4 Fault current waveforms for CA fault, 32km, 90°
Figure A-5 Fault current waveforms for BCG fault, 32km

Figure A-6 Fault current waveforms for CAG fault, 32km
Appendix B

MALTAB Program for WT analysis and Spectral Energy calculation

```matlab
filepath='C:\Users\niulv\Desktop\thesis_all\Atp06\new phaseselection\aground';

%Change the file folder and file name as necessary
faulttype='Aground';
filename='aground16kmvmin';

%Read the Data file
temp=csvread(fullfile(filepath,'\',faulttype,'\',filename,'.csv'),1,0);
A=temp(1:800,2);
B=temp(1:800,3);
CC=temp(1:800,4);

%Use Db4 to perform the WT analysis
[C,L]=wavedec(A,10,'db4');
C=C';
AA10 = wrcoef('a',C,L,'db4',10);
AD=zeros(10,length(AA10));
for jj=1:10
    AD(jj,:) = wrcoef('d',C,L,'db4',jj);
end

[C,L]=wavedec(B,10,'db4');
C=C';
BA10 = wrcoef('a',C,L,'db4',10);
BD=zeros(10,length(BA10));
for jj=1:10
    BD(jj,:) = wrcoef('d',C,L,'db4',jj);
end

[C,L]=wavedec(CC,10,'db4');
C=C';
CA10 = wrcoef('a',C,L,'db4',10);
CD=zeros(10,length(CA10));
for jj=1:10
    CD(jj,:) = wrcoef('d',C,L,'db4',jj);
end

%Calculate the spectral Energy
MM=length(Energycal_window1_2(AD(1,:)));
y=zeros(30,MM);
for i=1:10
    y(i,:)=Energycal_window1_2(AD(i,:));
end
for i=11:20
    y(i,:)=Energycal_window1_2(BD(i-10,:));
end
for i=21:30
    y(i,:)=Energycal_window1_2(CD(i-20,:));
end
```

181
%Sub-program for calculating spectral energy
function a=Energycal_window1_2(xx)

%Define the window size
WL=20;

%Calculate the spectral energy
N=fix(length(xx)/WL);
if N>length(xx)/WL
    N=N-1;
end
%a=zeros(1,150);
a=zeros(1,N);
for i=1:N
    for j=1:WL
        %a(1,i)=a(1,i)+xx(WL*(i-1)+j)^2;
        a(1,i)=xx(WL*(i-1)+j)^2;
        a(1,i)=xx(WL*(i-1)+j)^2;
    end
end
end
MATLAB program for realizing the threshold for the fault detection.

```matlab
function bb=Judge_Fault_Type103(aa)
% number
jj=1;
Count=0;
% External or internal Count
EX=0;
IN=0;
% Fault Type
Fault_ex=0;
Fault_in=0;
% New output, aa is the input
bb=aa;
% Threshold
TH1=0.5;
TH2=5.5;
% Criteria for judging the fault
N1=4;
N2=4;
% Identify the initial fault

while (1)
  % External or internal Count
  EX=0;
  IN=0;
  for ii=jj:length(aa)

    if aa(ii)<TH1
      bb(ii)=0;
      if EX==N1 | IN==N1
        break;
      else
        EX=0;
        IN=0;
      end
    end
    EX=0;
    IN=0;
    Count=Count+1;
    continue;
    else if aa(ii)>=TH1 && aa(ii)<TH2
      if EX==N1
        break;
      else if IN==N1
        break;
      else if IN>=0
        IN=0;
      end
      end
      end
      bb(ii)=1;
      Count=Count+1;
      EX=EX+1;
      continue;
      else if aa(ii)>=TH2
        if IN==N1
```
break;
    else if EX==N1
    break;
    else if EX>0
    EX=0;
    end
    end
end
bb(ii)=10;
Count=Count+1;
IN=IN+1;
continue;
end
end
end

% Determine the initial fault
if EX==4
    Fault_ex=Fault_ex+1;
    if Fault_in==1
        Fault_in=0;
    end
    faulttype='Initial: External error possible'
else if IN==4
    Fault_in=Fault_in+1;
    if Fault_ex==1
        Fault_ex=0;
    end
    faulttype='Initial: Internal error possible'
end
end
if Fault_ex==2
    faulttype='Final: External error'
    break
else if Fault_in==2
    faulttype='Final: Internal error'
    break
else if ii==length(aa)
    faulttype='Data is too few for judging the fault'
    break
end
end
jj=ii;
end

bb=bb(1:Count);
end
Related Publications


