

TUNNELING-INDUCED GROUND MOVEMENT AND BUILDING DAMAGE
PREDICTION USING HYBRID ARTIFICIAL NEURAL NETWORKS

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I dedicated this thesis to my beloved father and mother for their support and encouragement.

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ABSTRACT

The construction of tunnels in urban areas may cause ground displacement which distort and damage overlying buildings and services. Hence, it is a major concern to estimate tunneling-induced ground movements as well as to assess the building damage. Artificial neural networks (ANN), as flexible non-linear function approximations, have been widely used to analyze tunneling-induced ground movements. However, these methods are still subjected to some limitations that could decrease the accuracy and their applicability. The aim of this research is to develop hybrid particle swarm optimization (PSO) algorithm-based ANN to predict tunneling-induced ground movements and building damage. For that reason, an extensive database consisting of measured settlements from 123 settlement markers, geotechnical parameters, tunneling parameters and properties of 42 damaged buildings were collected from Karaj Urban Railway project in Iran. Based on observed data, the relationship between influential parameters on ground movements and maximum surface settlements were determined. A MATLAB code was prepared to implement hybrid PSO-based ANN models. Finally, an optimized hybrid PSO-based ANN model consisting of eight inputs, one hidden layer with 13 nodes and three outputs was developed to predict three-dimensional ground movements induced by tunneling. In order to assess the ability and accuracy of the proposed model, the predicted ground movements using proposed model were compared with the measured settlements. For a particular point, ground movements were obtained using finite element model by means of ABAQUS and the results were compared with proposed model. In addition, an optimized model consisting of seven inputs, one hidden layer with 21 nodes and one output was developed to predict building damage induced by ground movements due to tunneling. Finally, data from damaged buildings were used to assess the ability of the proposed model to predict the damage. As a conclusion, it can be suggested that the newly proposed PSO-based ANN models are able to predict three-dimensional tunneling-induced ground movements as well as building damage in tunneling projects with high degree of accuracy. These models eliminate the limitations of the current ground movement and building damage predicting methods.

ABSTRAK

Pembinaan terowong di kawasan bandar mungkin boleh menyebabkan sesaran tanah yang mengakibatkan kerosakan kepada bangunan atas serta perkhidmatan. Oleh itu, ramalan pergerakan tanah dan juga menilai tahap kerosakan bangunan akibat pembinaan terowong merupakan satu kepentingan utama bagi menangani masalah tersebut. Rangkaian Neural Buatan (ANN) yang memberikan anggaran fungsi tidak linear fleksibel telah digunakan dengan meluas untuk menganalisa pergerakan tanah disebabkan oleh pembinaan terowong. Namun begitu, kaedah-kaedah ini masih lagi tertakluk kepada batas-batas tertentu yang mengurangkan kejituan dan keterterapan kaedah-kaedah tersebut. Tujuan kajian ini dijalankan adalah untuk membina satu rangkaian hibrid yang terdiri daripada ANN dan algoritma pengoptimuman kerumunan zarah (PSO) bagi meramal pergerakan tanah dan kerosakan bangunan yang disebabkan oleh pembinaan terowong. Lantaran itu, satu pangkalan data yang meluas telah dibangunkan merangkumi ukuran enapan daripada 123 penanda enapan, parameter geoteknik, parameter penerowongan dan sifat-sifat 42 bangunan yang mengalami kerosakan telah dikumpulkan dari projek Kereta Api Bandar Karaj di negara Iran. Berdasarkan data yang dicerap, hubungan antara parameter-parameter dominan yang menyebabkan pergerakan tanah dan enapan permukaan tanah maksimum telah ditentukan. Kod MATLAB telah disediakan untuk melaksanakan model-model hibrid ANN berasaskan PSO. Akhirnya, satu model pengoptimuman hibrid ANN berasaskan PSO yang mempunyai lapan input, satu lapisan tersembunyi mengandungi 13 nod dan tiga output telah dibangunkan untuk meramal pergerakan tanah tiga dimensi akibat pembinaan terowong. Untuk tujuan penilaian kemampuan dan kejituan model yang dicadangkan, nilai-nilai pergerakan tanah yang diramal menggunakan model cadangan tersebut telah dibandingkan dengan nilai enapan yang telah diukur. Bagi satu titik yang khusus, nilai pergerakan tanah telah diperolehi melalui model unsur terhingga dengan menggunakan perisian ABAQUS, dan hasilnya telah dibandingkan dengan model cadangan. Sebagai tambahan, satu model teroptimum yang terdiri daripada tujuh input, satu lapisan tersembunyi mengandungi 21 nod dan satu output telah dibangunkan untuk meramal kerosakan bangunan akibat pergerakan tanah yang disebabkan oleh pembinaan terowong. Akhir sekali, data dari bangunan yang mengalami kerosakan telah digunakan untuk menilai kemampuan model cadangan untuk meramal kerosakan bangunan tersebut. Kesimpulannya, model cadangan baru ANN yang berdasarkan PSO berkemampuan untuk meramal pergerakan tanah tiga dimensi dan kerosakan bangunan yang disebabkan oleh pembinaan terowong dengan tahap kejituan yang tinggi. Model-model baru tersebut dapat menyingkirkan batasan pada kaedah sedia ada bagi ramalan pergerakan tanah dan kerosakan bangunan.

TABLE OF CONTENTS

CHAPTER	TITLE	PAGE
	DECLARATION	ii
	DEDICATION	iii
	ACKNOWLEDGMENTS	iv
	ABSTRACT	v
	ABSTRAK	vi
	TABLE OF CONTENTS	vii
	LIST OF TABLES	xiii
	LIST OF FIGURES	xv
	LIST OF ABBREVIATIONS	xxiv
	LIST OF SYMBOLS	xxv
	LIST OF APPENDICES	xxviii
1	INTRODUCTION	1
	1.1 Background of the Study	1
	1.2 Statement of the Problem	3
	1.3 Research Objectives	5
	1.4 Significance of Research	6
	1.5 Scope and Limitation of the Study	7
	1.6 Outline of Thesis	7
2	LITERATURE REVIEW	10
	2.1 Introduction	10
	2.2 Prediction of the Ground Deformations	10
	2.2.1 Empirical Methods	11

2.2.1.1	Surface Settlements in Transverse Direction	12
2.2.1.2	Surface Settlements in Longitudinal Direction	16
2.2.1.3	Subsurface Settlement and Horizontal Displacement	19
2.2.2	Analytical Methods	21
2.2.2.1	Virtual Image Technique	21
2.2.2.2	Complex Variable Method	27
2.2.2.3	Airy Function Technique	28
2.2.3	Laboratory Model Test	33
2.2.4	Numerical Analyses	38
2.2.4.1	Two Dimensional Analyses	39
2.2.4.2	Three Dimensional Analyses	40
2.2.5	Artificial Intelligence Approach	45
2.2.5.1	Application of ANNs on Sequential Tunneling	47
2.2.5.2	Application of ANNs on Mechanized Tunneling	56
2.2.5.3	Application of ANNs on Prediction of Tunnel Convergence	62
2.3	Building Damage Assessment	63
2.3.1	Definition of Distortion Parameters	64
2.3.2	Category of Building Damage	66
2.3.3	Assessment Methods	68
2.3.3.1	Empirical Approach	68
2.3.3.2	Semi-Analytical Approach	70
3	ARTIFICIAL NEURAL NETWORKS AND PARTICLE SWARM OPTIMIZATION	78
3.1	Introduction	78
3.2	Artificial Neural Networks	79
3.2.1	Biological and Artificial Neurons Networks	79
3.2.2	Type of ANNs	81

	3.2.2.1 Feedforward ANNs	82
	3.2.2.2 Recurrent ANNs	84
	3.2.3 Neural Network Modeling	85
	3.2.4 Learning Processes using BP Algorithm	89
	3.2.5 Network Architecture	90
3.3	Optimized ANNs	91
	3.3.1 Optimization Techniques	92
	3.3.2 Global Optimization Techniques	92
	3.3.2.1 Comparison between GA and PSO Algorithms	95
	3.3.3 Theory and Background of PSO Algorithm	96
	3.3.4 The Procedure of PSO Algorithm	97
	3.3.5 Hybrid PSO-Based ANN	99
4	RESEARCH METHODOLOGY	101
	4.1 Introduction	101
	4.2 Procedure of the Research	101
	4.3 Literature Review	103
	4.4 Data Collection	104
	4.5 Computer Programming	106
	4.6 Determining Input and Output Parameters	106
	4.7 Determining the Optimal PSO Parameters and Networks Architecture	107
	4.8 Prediction of Surface Settlement and Building damage	107
	4.9 Validation	107
	4.9.1 FE Analysis of Tunnel Construction	108
	4.10 Verification	109
5	CASE STUDY: KARAJ URBAN RAILWAY PROJECT, IRAN	111
	5.1 Introduction	111
	5.2 Project Description	111
	5.3 Geological Condition	113
	5.4 Geotechnical Studies	114

5.4.1	Subsurface Exploration	116
5.4.2	Geotechnical Field Testing	116
5.4.3	Geotechnical Laboratory Testing	117
5.4.3.1	Soil Physical Tests	117
5.4.3.2	Soil Mechanical Tests	120
5.5	Tunnel Properties and Tunneling Method	121
5.6	Instrumentation Monitoring Program	122
6	GROUND MOVEMENTS PREDICTION	126
6.1	Introduction	126
6.2	Influential Parameters on Tunneling-Induced Ground Movements	127
6.2.1	Geological and Geotechnical Properties	128
6.2.2	Tunnel Geometry and Tunneling Operation	134
6.3	Input and Output Parameters	136
6.4	Ground Movements Prediction Using BPANN	138
6.4.1	Computer Programming	138
6.4.2	Network Design	141
6.5	Ground Movements Prediction Using Hybrid PSO-Based ANN	145
6.5.1	Computer Programming	146
6.5.2	Network Design	148
6.5.2.1	Swarm Size	149
6.5.2.2	Termination Criteria	151
6.5.2.3	Coefficients of Velocity Equation	152
6.5.2.4	Inertia Weight	154
6.5.2.5	Network Architecture	155
6.6	Comparison Between BPANN and PSO-Based ANN Results	160
6.7	Analysis of Tunneling-Induced Surface Settlement using Proposed PSO-Based ANN Model	165
6.8	Validation	172
6.8.1	FE Modeling Results	177

6.8.2	Comparison between Results Obtained by Proposed PSO-Based ANN and FE Simulation	179
7	BUILDING DAMAGE ASSESSMENT	182
7.1	Introduction	182
7.2	Building Damage Assessment	183
7.2.1	Input and Output Data	186
7.2.2	Network Design	188
7.2.2.1	Swarm Size and Termination Criteria	189
7.2.2.2	Coefficients of Velocity Equation	191
7.2.2.3	Inertia Weight	192
7.2.2.4	Network Architecture	193
7.3	Prediction of Building Damage	198
7.3.1	Building Damage Prediction using PSO- Based ANN Model	200
7.3.2	Building Damage Prediction using Deep Beam Theory	201
7.3.3	Validation	202
8	CONCLUSION AND RECOMMENDATIONS	203
8.1	Introduction	203
8.2	Conclusion	203
8.3	Contributions of Research	205
8.3.1	Ground Movements	205
8.3.2	Building Damage	205
8.4	Recommendation for Future Works	206
	REFERENCES	207
	Appendices A-F	225-334

LIST OF TABLES

TABLE NO.	TITLE	PAGE
2.1	Summary of previous works on application of ANNs in tunneling problems	45
2.2	Performance of the ANN and statistical models (Grima et al., 2000)	57
2.3	Category of building damage (after Burland et al., 1977)	67
2.4	Characteristic limits of building damage (Skempton and MacDonald, 1956)	68
2.5	Characteristic admissible and danger limits of building damage (Bjerrum, 1963)	69
2.6	Critical value of tilt for low-rise buildings (Charles and Skinner, 2004)	70
2.7	Relationship between category of damage and limiting tensile strain (after Boscardin and Cording 1989)	73
2.8	Relation between category of damage and tilt based on concept of limiting tensile strain for $L/H = 1$ (Namazi and Mohamad, 2012b)	76
3.1	Terminology between biological neurons and ANNs (Haykin, 1999)	81
3.2	Comparison of metaheuristics methods (after Kitagawa et al., 2004)	94
4.1	Collected Data from KUR Project	105
5.1	Geotechnical field testing results for Phase I of KUR	117
5.2	Description of soil layers in Phase I of KUR (ZPCE, 2005; DKPCE 2005; IKCE 2005)	118

5.3	Physical Properties of soil layers in Part I of KUR (ZPCE, 2005)	119
5.4	Physical Properties of soil layers in Part II of KUR (DKPCE, 2005)	119
5.5	Physical Properties of soil layers in Part III of KUR (IKCE, 2005)	119
5.6	Mechanical Properties of soil layers in Part I of KUR (ZPCE, 2005)	120
5.7	Mechanical Properties of soil layers in Part II of KUR (DKPCE, 2005)	120
5.8	Mechanical Properties of soil layers in Part III of KUR (IKCE, 2005)	120
6.1	Input parameters in surface settlement prediction	137
6.2	Output parameters in surface settlement prediction	138
6.3	Performance of trained BPANN models	142
6.4	Sensitivity analysis results for velocity equation coefficient	153
6.5	Performance of trained PSO-based ANN models	156
6.6	Geotechnical and tunneling properties at the measurement points	166
6.7	Measured and predicted surface settlements in transverse direction at various locations	172
6.8	Geotechnical properties of soil layers between chainage 3+300 km and 3+400 km in KUR Project	173
6.9	Measured and predicted surface settlements in transverse direction	180
7.1	Summary of reported building damage in KUR project	185
7.2	Input and output parameters used for prediction of building damage	188
7.3	The results of sensitivity analyses for velocity equation coefficient	191
7.4	Performance of trained PSO-based ANN models	194
7.5	Properties of the selected damaged buildings and measured surface settlements and crack width	199

7.6	Geotechnical and tunneling properties close to the FCI building	200
7.7	Category of building damage obtained by deep beam theory from Burland et al. (1977)	201
7.8	Category of building damage obtained by the PSO-based ANN model, deep beam theory and measured values	202

LIST OF FIGURES

FIGURE NO.	TITLE	PAGE
2.1	Typical settlement profile induced by tunneling (after Attewell <i>et al.</i> , 1986)	11
2.2	Transverse settlement trough	13
2.3	Relationship between width of settlement trough and dimensionless depth of tunnel, $z_0/2R$, for different ground conditions (after Peck, 1969)	13
2.4	Relationship between volume loss and volume of surface settlement trough (after Standing and Burland, 2006)	14
2.5	Longitudinal settlement trough (after Attewell and Woodman, 1982)	17
2.6	Definition and quantity of G (after Attewell <i>et al.</i> , 1982)	18
2.7	Variation of K with depth in clay (Mair <i>et al.</i> , 1993)	19
2.8	Distribution of horizontal surface displacement and strain (after Franzius, 2003)	20
2.9	Steps in the virtual image analysis (Sagaseta, 1987)	22
2.10	(a) Ground loss and ovalization of a tunnel (b) singularity and its image (Verruijt and Booker, 1996)	23
2.11	Definition of the gap parameter (Rowe and Kack, 1983)	24
2.12	Simulation of ground loss (Lee <i>et al.</i> , 1992)	25
2.13	Half-plane with hole (Strack, 2002)	28
2.14	Shallow tunnel (Chou and Bobet, 2002)	29
2.15	Ground deformation pattern around the tunnel (Park, 2005)	30
2.16	Deep and shallow circular tunnel (Park, 2004)	31
2.17	Boundary condition of prescribed displacement (Park, 2004)	32

2.18	Components of final tunnel deformation (Pinto and Whittle, 2006)	33
2.19	Centrifuge tunnel modeling (Chambon and Corte, 1994)	34
2.20	Displacement versus internal tunnel pressure from centrifuge tunnel modeling (Chambon and Corte, 1994)	34
2.21	Test setup and failure mechanism resulting from air pressure reduction at the tunnel face (Sterpi <i>et al.</i> , 1996)	35
2.22	Progressive development of settlement trough obtained by polystyrene foam in model test (Sharma <i>et al.</i> , 2001)	36
2.23	Observed failure pattern from centrifuge test (Kamata and Masimo, 2003)	36
2.24	Settlement troughs developed from the construction of two parallel tunnels (Champan <i>et al.</i> , 2006)	37
2.25	Measured and predicted surface settlement induced by twin-tunnel in overconsolidated clay (Divall and Goodey, 2012)	38
2.26	Longitudinal settlement troughs for different excavation methods in the first excavation step (Vermeer <i>et al.</i> , 2002).	42
2.27	Development of the longitudinal settlement trough in three-dimensional FE analysis (Möller <i>et al.</i> , 2003)	42
2.28	Transverse settlement troughs for different stages of two-dimensional and three-dimensional analyses compared with field data (Franzius <i>et al.</i> , 2005)	43
2.29	Transverse settlement troughs for two-dimensional and three-dimensional analyses at different K_0 values (Franzius <i>et al.</i> , 2005)	44
2.30	General ANN model with input and output parameters to predict maximum surface settlement (Shi <i>et al.</i> , 1998)	48
2.31	Measured and predicted results from the modular ANN (Shi <i>et al.</i> , 1998)	49
2.32	The optimal architecture of ANN proposed by Kim <i>et al.</i> (2001)	50
2.33	Comparison between measured and predicted air losses (Javadi, 2006)	51

2.34	Combination of ANN and FE approaches to design and construct shallow NATM tunnels (Lee <i>et al.</i> , 2007)	51
2.35	Comparison of FE and ANN results with field measured data (Lee <i>et al.</i> , 2007)	52
2.36	Comparison between measured data and predicted values for tests datasets (Santos Jr. and Celestino, 2008)	53
2.37	Rheological parameter estimation technique (Guan <i>et al.</i> , 2009)	54
2.38	Comparison of the results obtained by monitoring data, numerical simulation and ANN analysis (Guan <i>et al.</i> , 2009)	54
2.39	Error between predicted and actual production rates of tunnel construction using drill and blast method (Lau <i>et al.</i> , 2010)	55
2.40	The neuro-fuzzy approach to simulate TBM performance (Grima <i>et al.</i> , 2000)	56
2.41	Structure of ANN model to predict surface settlement induced by EBP shield tunneling (Suwansawat and Einstein, 2006)	58
2.42	Training and testing results from ANN, trained with all data from tunnel sections (Suwansawat and Einstein, 2006)	59
2.43	Network architecture to predict maximum settlement above a tunnel (Neaupane and Adhikari, 2006)	60
2.44	Comparison between predicted horizontal movement by BPANN and Loganathan and Poulos (1998) method for Heathrow Expressway Tunnel (Neaupane and Adhikari, 2006)	60
2.45	Comparison between relative errors obtained from ANFIS and other methods (Hou <i>et al.</i> , 2009)	61
2.46	RMSE and MAE errors comparison for wavenet and neural network methods (Pourtaghi and Lotfollahi-Yaghin, 2012)	62
2.47	Comparison between predicted and measured values of the tunnel convergence using MLP network (Mahdevari and Torabi, 2012)	63
2.48	Building and ground movement parameters (after Franzius, 2003)	65
2.49	Twist definition (after Franzius, 2003)	66

2.50	Cracking of a simple beam in bending and shear (Burland and Wroth, 1975)	71
2.51	Relationship between Δ/L_{lim} and L/H due to combined bending and shear deformation having neutral axis at the bottom of the beam (Burland and Wroth, 1975)	72
2.52	Prediction of damage based on angular distortion and horizontal strain (Boscardin and Cording, 1989)	73
2.53	Relative relationship of damage category, deflection ratio and horizontal tensile strain (after Burland, 1997)	74
2.54	Category of damage based on horizontal strain and deflection ratio for different value of tilt (Namazi and Mohamad, 2012b)	76
3.1	Biological neuron (Fausett, 1993)	80
3.2	Details of a neuron (Mehrotra <i>et al.</i> , 1997)	81
3.3	A feedforward MLP network (after Haykin, 1999)	83
3.4	Three layers feedforward MLP network (Beale <i>et al.</i> , 2010)	83
3.5	A Hopfield network (Picton, 2000)	84
3.6	Schematic diagram of neurons and transmission processes (Suwansawat and Einstein, 2006)	85
3.7	Unit step activation function (after Rojas, 1996)	86
3.8	Linear activation function (after Rojas, 1996)	87
3.9	Sigmoid activation function (after Rojas, 1996)	88
3.10	Tangent sigmoid activation function (after Rojas, 1996)	88
3.11	Sigmoid function with different slope parameter (after Rojas, 1996)	89
3.12	Directions of two basic signal flows in a multi-layer perceptron (after Haykin, 2008)	90
3.13	Standard flow chart of PSO (after Kennedy and Eberhart, 1995)	98
3.14	Learning process of PSO-based ANN model (Kuok <i>et al.</i> , 2009)	100
4.1	Research approach	102
4.2	Flowchart of the research methodology	103
4.3	Verification procedure on the PSO-based ANN models	110
5.1	Location of Karaj city, Iran	112

5.2	Schematic view of KUR Line No.2 and the location of subway stations (after DKPCE, 2005)	113
5.3	Project phases in Line No.2 of KUR (after DKPCE, 2005)	115
5.4	Depth of the tunnel in KUR project (after DKPCE, 2005)	121
5.5	Tunnel dimensions and construction sequence (after DKPCE, 2005)	122
5.6	Schematic plan of settlement markers location in KUR project (after Tunnel Rod Construction Consulting Engineers, 2010)	123
5.7	Building crack measurement in KUR project	124
5.8	Typical monitoring plan in KUR project (after Tunnel Rod Construction Consulting Engineers, 2010)	125
6.1	Influential parameters causing ground movements	127
6.2	Location of settlement markers and the boreholes used in determining the geotechnical properties	129
6.3	The relationship between average SPT N-values and measured maximum surface settlement in KUR project	130
6.4	The relationship between soil cohesion and measured maximum surface settlement in KUR project	131
6.5	The relationship between friction angle and measured maximum surface settlement in KUR project	132
6.6	The relationship between unit weight and measured maximum surface settlement in KUR project	132
6.7	The relationship between soil elastic modulus and measured maximum surface settlement in KUR project	133
6.8	The relationship between Poisson's ratio and measured maximum surface settlement in KUR project	133
6.9	The relationship between tunnel depth and measured maximum surface settlement in KUR project	135
6.10	The relationship between advancement rate and measured maximum surface settlement in KUR project	136
6.11	BPANN development process	139
6.12	Correlation coefficient for trained BPANN models	143
6.13	Mean square error for trained BPANN models	143

6.14	Performance of the selected BPANN using training datasets	144
6.15	Performance of the selected BPANN using testing datasets	144
6.16	Training performance in different epochs	145
6.17	PSO-based ANN model development process	147
6.18	The relationship between swarm size and correlation coefficient	150
6.19	The relationship between swarm size and MSE	150
6.20	Total consumed time to train the network with different swarm sizes	150
6.21	Convergence process for different swarm sizes	152
6.22	Comparison between the coefficients of correlation of training and testing at different inertia weights in PSO-based ANN models	155
6.23	Comparison between the MSE of training and testing at different inertia weights in PSO-based ANN models	155
6.24	Correlation coefficient for trained PSO-based ANN models	157
6.25	Mean square error for trained PSO-based ANN models	158
6.26	Performance of the selected PSO-based ANN model using training datasets	159
6.27	Performance of selected PSO- based ANN model using testing datasets	159
6.28	Structure of the selected PSO-based ANN model for ground movements prediction	160
6.29	Coefficient of correlation for training datasets in different BPANN and PSO-based ANN models	161
6.30	Coefficient of correlation for testing datasets in different BPANN and PSO-based ANN models	161
6.31	The difference between coefficient of correlation in training and testing datasets for BPANN and PSO-based ANN models	162

6.32	Mean square error for training datasets in BPANN and PSO-based ANN models	163
6.33	Mean square error for testing datasets in BPANN and PSO-based ANN models	163
6.34	The difference between values of mean square error for training and testing datasets in BPANN and PSO-based ANN models	164
6.35	Transverse settlement trough obtained by proposed PSO-based ANN model at Point 1	167
6.36	Longitudinal settlement trough obtained by proposed PSO-based ANN model at Point 1	167
6.37	Three dimensional settlement trough obtained by proposed PSO-based ANN model at Point 1	168
6.38	Transverse settlement trough obtained by proposed PSO-based ANN model at Point 2	169
6.39	Longitudinal settlement trough obtained by proposed PSO-based ANN model at Point 2	169
6.40	Three dimensional settlement trough obtained by proposed PSO-based ANN model at Point 2	170
6.41	Transverse settlement trough obtained by proposed PSO-based ANN model at Point 3	170
6.42	Longitudinal settlement trough obtained by proposed PSO-based ANN model at Point 3	171
6.43	Three dimensional settlement trough obtained by proposed PSO-based ANN model at Point 3	171
6.44	Sky view between chainage 3+300 km and 3+400 km in Shahid Beheshti Street in Karaj	172
6.45	Tunnel depth and dimensions, and soil layers in the study area	174
6.46	Three-dimensional FE model of KUR tunnel in ABAQUS	175
6.47	Top heading excavation of the KUR tunnel in ABAQUS	176
6.48	Bench excavation of the KUR tunnel in ABAQUS	176
6.49	Ground movements around the tunnel and at the surface obtained by FE analysis	178

6.50	Transverse settlement trough obtained by finite element analysis	178
6.51	Longitudinal settlement trough obtained by FE analysis	179
6.52	Comparison between transverse settlement troughs obtained by FE analysis, PSO-based ANN model and measured data at Point 2	180
6.53	Comparison between longitudinal settlement troughs obtained by FE analysis, PSO-based ANN model and measured data	181
7.1	Tunneling-induced cracks in the interior of a building next to KUR Tunnel	183
7.2	Tunneling-induced cracks in the exterior of a building next to KUR Tunnel	184
7.3	Moderate crack occurred due to tunneling at the staircase of a commercial building next to KUR Tunnel	184
7.4	Coefficient of correlation for models with different swarm size	189
7.5	Training consumed time for models with different swarm size	189
7.6	Convergence processes for different swarm sizes	190
7.7	Comparison between the coefficients of correlation of training and testing at different inertia weights in PSO-based ANN models	192
7.8	Comparison between the MSE of training and testing at different inertia weights in PSO-based ANN models	193
7.9	Coefficient of correlation for trained PSO-based ANN models	195
7.10	Mean square error for trained PSO-based ANN models Performances of the selected PSO-based ANN model using training and testing datasets	195
7.11	Performance of the selected model using training datasets	196
7.12	Performance of the selected model using testing datasets	196
7.13	Concordance between actual and predicted values for training datasets	197

7.14	Concordance between actual and predicted values for testing datasets	197
7.15	Structure of the selected PSO-based ANN model to predict tunneling-induced building damage	198
7.16	The cracks in Sarvenaz Residential building	199
7.17	The crack in Financial and Credit Institution Building	200

LIST OF ABBREVIATIONS

AI	-	Artificial Intelligence
ANFIS	-	Adaptive Neuro-fuzzy Inference System
ANN	-	Artificial Neural Network
BP	-	Backpropagation
BPANN	-	Backpropagation Artificial Neural Network
CMAC	-	Cerebellar Model Articulation Control
DKPCE	-	Darya KhakPey Consulting Engineers
EPB	-	Earth Pressure Balance
FCI	-	Financial and Credit Institution
FE	-	Finite Element
GA	-	Genetic Algorithm
GMDH	-	Group Method of Data Handling
IKCE	-	Iran Khak Consulting Engineers
KUR	-	Karaj Urban Railway
LVQ	-	Learning Vector Quantization
MAE	-	Mean Absolute Error
MC	-	Mohr-Coulomb
MLP	-	Multi-Layer Perceptron
MSE	-	Mean Square Error
NATM	-	New Austrian Tunneling Method
PSO	-	Particle Swarm Optimization
RBF-ANN	-	Radial Basis Function Artificial Neural Networks
RMSE	-	Root Mean Square Error
SPT	-	Standard Penetration Test
SR	-	Sarvenaz Residential
ZPCE	-	Zamin Pazhooh Consulting Engineers

LIST OF SYMBOLS

S_v	-	Vertical settlement
x	-	Distance from the tunnel center line
$S_{v,max}$	-	Maximum surface settlement
i	-	Horizontal distance from tunnel center line to inflection point
V_L	-	Ground loss
z_0	-	Tunnel depth
S_c	-	Vertical settlement at the tunnel crown
k	-	Empirical constant
x_i	-	Initial position of the tunnel
x_f	-	Location of the tunnel face
S_h	-	Horizontal ground movement
ε_h	-	Horizontal strain
ε	-	Uniform radial ground loss
δ	-	Long term ground deformation
R	-	Tunnel radius
H	-	Depth
m	-	Auxiliary elastic constant
ϑ	-	Poisson's ratio
G_p	-	Physical gap
δ_l	-	Clearance required for erection of the lining
u_{3D}^*	-	Three dimensional elasto-plastic deformation
ω	-	Quality of workmanship
u_x	-	Horizontal displacements
u_z	-	Vertical displacements
ρ	-	Ovalization
α	-	Coefficient in elastic region
μ	-	Elastic constant of shear modulus

$\varphi(z)$	-	Complex variable
$\psi(z)$	-	Complex variable
$\varphi'(z)$	-	Notation
E	-	Young's modulus
γ	-	Unit weight
γ_b	-	Buoyant soil unit weight
γ_w	-	water unit weight
k_0	-	Coefficient of earth pressure at rest
$\delta S_{v,max}$	-	Relative settlement
θ_{max}	-	Rotation of slope
Δ	-	Relative deflection
Δ/L	-	Deflection ratio
ω	-	Tilt
β	-	Angular distortion
r_{xz}	-	Curvature of the surface
L	-	Length of the building
B	-	Width of the building
G	-	Shear modulus
$\varepsilon_{b,max}$	-	Maximum extreme bending strain
$\varepsilon_{d,max}$	-	Maximum diagonal strain
ε_{br}	-	Extreme fibre strain
ε_{dr}	-	Diagonal tensile strain
x_i	-	Input parameter
$w_{j,i}$	-	Weight of the link
b_j	-	Bias
y_k	-	Output of the network
w	-	Slope parameter
$f(x)$	-	Objective function
\vec{v}_{new}	-	New velocity
\vec{v}	-	Current velocity
\vec{p}_{new}	-	New position
\vec{p}	-	Current position
C_1	-	Pre-defined coefficient
C_2	-	Pre-defined coefficient
\vec{p}_{best}	-	Personal best position

\vec{gbest}	-	Global best position
w	-	Inertia weight
N	-	Number of patterns in the testing set
O	-	Output produced by the network
t	-	Target
N_s	-	Swarm size
$[D_s]$	-	Integer part of the particles dimension

LIST OF APPENDICES

APPENDIX	TITLE	PAGE
A	MATLAB Codes	225
B	Performance of Trained BPANN Models to Predict Ground Movements	234
C	Results of Sensitivity Analyses on PSO Parameters to Predict Ground Movements	254
D	Performance of Trained Models using Hybrid PSO-Based ANN Models to Predict Ground Movements	279
E	Results of Sensitivity Analyses on PSO Parameters to Predict Building Damage	298
F	Performance of Trained Models using PSO-Based ANN Models to Predict Building Damage	316

CHAPTER 1

INTRODUCTION

1.1 Background of the Study

Over the last few years, the world has witnessed an enormous growth of the urban population. The speed and the scale of the population growth in urban areas are among the most difficult challenges to some countries. This growth of the urban areas has resulted in increased demand for infrastructures. Subsurface structures such as tunnels and underground metro stations became definitive choice to overcome the congestion at the ground surface, while urban environments became more limited. Although underground structures have been effective in addressing the congestions at the surface, some problems and challenges still exist related to the tunneling in urban environment.

The estimation of the environmental impacts of the tunnel construction is one of the most important steps in tunnel design in urban areas. Although construction of tunnels in urban areas has various long term benefits, it may also cause important environmental issues. Surface settlement is a very significant impact of tunneling in urban areas that can cause considerable damages to adjacent buildings and roads, and therefore increase the maintenance costs. Hence, it is a major concern in the underground works to estimate tunneling-induced ground movements and also assess the building damage induced by ground movements due to tunneling.

In general, tunneling-induced ground movements are caused by three components; the immediate settlements due to tunnel excavation, deformation of tunnel lining and consolidation. Immediate settlement, as the major settlement induced by tunneling, is a function of the tunnel depth and diameter, geological and geotechnical conditions, and construction procedure. Deformation of the tunnel lining has an insignificant role in creating surface settlement and is usually negligible (Lee *et al.*, 1992). Long term settlement due to primary and secondary consolidation takes place in the saturated soils and groundwater conditions. Based on empirical, analytical and numerical approaches, several methods have been developed by previous researchers to predict surface settlements due to tunneling.

An empirically derived relationship has been introduced by Peck (1969) based on observation of transverse settlement trough in several tunneling project. He assumed the shape of transverse settlement trough like a normal distribution curve. This method was accepted as a fundamental form of empirical methods and became the basis for other researchers such as Cording and Hansmire (1975) and O'Reilly and New (1982). Moreover, Attewell and Woodman (1982) also utilized the stochastic theory to predict longitudinal surface settlement. Analytical methods have been developed based on fundamental equations of elastic theory. Several research have been conducted to predict surface settlements by means of analytical methods as in Sagaseta (1987), Verruijt and Booker (1996), Loganathan and Poulos (1998) and Park (2004). In the last decades, numerical methods have been developed due to increasing in powerful computers beside the capability of the numerical methods in analysing the complex geometrical conditions. Extensive research have been conducted to estimate tunneling-induced ground movements using numerical analysis (e.g. Lee *et al.*, 1992; Vermeer *et al.*, 2002; and Alessandra *et al.*, 2009).

In parallel with the development of prediction methods of ground movements, it has been hardly attempted to estimate building damage due to tunneling. Similar to empirical methods of surface settlement prediction, various case studies have been investigated (e.g. Skempton and MacDonald, 1956; Bjerrum, 1963; and Charles and Skinner, 2004) to establish a correlation between distortion parameters and the corresponding damage limits. In contrast to empirical methods,

the semi-analytical method has become more popular. This method was introduced by Burland and Wroth (1975) and further developed by other researchers such as Boscardin and Cording (1989). This method assumes that the onset of crack is associated with average tensile strain in the buildings and utilizes the linear-elastic deep beam to obtain the maximum tensile strain in the buildings.

All aforementioned methods to predict ground movements and building damage induced by tunneling assume the tunneling in “greenfield” conditions. In other words, these methods ignore the presence of surface structures and their effects on ground movements. In addition, all these studies are still faced with some limitations. Therefore, an effective method is required to be able to predict ground movements and building damages induced by tunneling, accurately.

In recent years, Artificial Neural Networks (ANNs) have been widely used to analyse geotechnical problems. An ANN is a flexible non-linear function approximation that figures out a relationship between given input-output data, in contrast to the empirical and statistical methods which need previous knowledge. Several attempts (e.g. Suwansawat and Einstein, 2006; Santos Jr and Celestino, 2008; and Boubou *et al.*, 2012) have been done to predict tunneling-induced ground movements using ANNs. Although ANNs are able to directly map input to output patterns and utilize all influential parameters in prediction of surface settlements, however still subjected to some limitation. Therefore, an effort is needed to reduce the limitations making ANNs more applicable and accurate to predict ground movements as well as building damage induced by tunneling.

1.2 Statement of the Problem

As mentioned earlier, numerous attempts have been done to predict and subsequently control the tunneling-induced ground movements due to the fact that the number of tunnels in urban areas is increasing. However, existing methods are faced with some limitations and cannot take into account of all the influential parameters in creating surface settlements. As a result, in many cases, the existing

methods are not accurate enough, whereas prediction of the exact amount of the maximum surface settlement and the shape of settlement troughs is important to estimate the potential risk of building damage induced by tunneling.

Empirically derived relationships have been mainly developed based on field observations obtained from hand mines or tunnels excavated using open faced shields. Therefore, these methods mainly consider more of geological conditions than tunneling operational parameters. Although these methods provide satisfactory results in determining settlement troughs, they tend to be misleading in estimating maximum surface settlement. Analytical methods assume ground as an initially isotropic, incompressible and homogeneous mass. These methods have been only developed for circular tunnels and therefore are inapplicable for non-circular tunnels under invariant geological conditions.

Finite element simulation usually obtains the settlement troughs shallower and wider than the field observations (Lee and Rowe, 1989; Gunn, 1993; Dasari *et al.*, 1996; Addenbrooke *et al.*, 1997). This limitation can be partly improved by using advanced soil constitutive models. However, the time and the cost for a full three dimensional analysis with advanced nonlinear soil constitutive models is substantial. In addition, accuracy of the result depends on the type and the size of mesh. ANNs employ training algorithms to be able to model complex relationships between inputs and output data. Backpropagation (BP) algorithm is the most common and well-known training algorithm that tries to adjust the network weights during learning process by reducing the error between input and output data. However, it has been proven that BP algorithm can easily converge to any local minimum (Gori and Tesi, 1992; Kröse and Smagt, 1996; Priddy and Keller, 2005), whereas the aim of simulation using ANNs is to find the global minimum of the error function. In addition, the convergence obtained from BP learning is very slow and BP cannot guarantee the convergence in learning.

In the case of building damage assessment, the existing methods assume the buildings infinitely flexible and follow the greenfield ground displacement. Therefore, these methods require separate numerical analyses to determine the

influence of building stiffness on ground displacements. Moreover, existing methods mostly determine building damages in two-dimensional condition, while building damage due to tunneling is exposed to three dimensional ground movements.

There is no doubt that the ground movements and building damage analysis would be more realistic if the measured data is used. According to the capabilities of artificial neural network to find a pattern among the input and output data, this method has the potential to be appropriate approach to predict ground movements induced by tunneling and building damages induced by ground movements due to tunneling, while its limitation is eliminated.

1.3 Research Objectives

The aim of the research is to develop a new model based on “hybrid particle swarm optimization (PSO) algorithm-based artificial neural network (ANN)” or “hybrid PSO-based ANN” to predict three-dimensional tunneling-induced ground movements and subsequently building damage induced by ground movements due to tunneling. This approach is able to cover all influential parameters on ground movements and building damages. In line with the aim of the research, the followings are the research objectives:

- i. To determine the relationship between influential parameters on ground movements and maximum surface settlement by analysing the behaviour of ground response related to tunneling
- ii. To predict three-dimensional ground movements induced by tunneling through a hybrid PSO-based ANN model
- iii. To determine the superiority of the proposed hybrid PSO-based ANN model as compared to pre-developed backpropagation artificial neural network by performing a substantial comparison between the obtained results
- iv. To predict building damage due to ground movement induced by tunneling using hybrid PSO-based ANN model

1.4 Significance of Research

Large numbers of tunnels are excavated in many big cities around the world. A major concern of engineers during excavation of tunnels in the populated areas is to know that the surface and underground structures and services are sufficiently safe from ground movements induced by tunnel excavation. Hence, a reliable method to predict surface settlements and consequently the risk of the damage to adjacent building is necessary. The importance of the study on ground movements induced by tunneling is associated with the safety and economic aspects of underground projects. The significant of research are as follows:

- i. This study demonstrates the relationships among the surface settlement induced by tunneling and influential parameters. Therefore, the outcomes of the study contribute better understanding towards the behaviour of the ground surface settlements related to tunneling.
- ii. The presented research considers the effects of the existing structures on the surface settlement, due to the fact that actual data are used to train the networks, whereas the existing methods predict surface settlement in greenfield condition. Therefore, the method developed from this research provides more realistic and accurate prediction.
- iii. In the model developed in this research, the ground movements induced by tunneling are simulated three-dimensionally, whereas empirical and analytical methods investigate the ground movements only in two dimensional and are usually applicable for specific type of tunnel. In contrast to the three-dimensional analysis of ground movements using advanced finite element tools that usually need much time to create and run a model, the presented model is practically useful to simulate ground movements three-dimensionally in detail within a short time.
- iv. The existing methods for assessing building damage provide a simple means of estimating the near surface displacements due to tunneling under greenfield condition, whereas a separate three dimensional analysis is required to investigate the effects of the building stiffness on the twist deformation. In contrast, the proposed model is able to estimate

tunneling-induced building damage, in a straightforward manner. This is a useful model to quantify the building damage using all the influential parameters in actual condition with reasonable accuracy.

1.5 Scope and Limitation of the Study

This research developed the model to predict tunneling-induced ground movements in soft soils above water table. As a limitation, the presented model is applicable for only NATM tunnels due to the fact that the model was trained using measured data obtained from Karaj Urban Railway Tunnel that was excavated using NATM technique. It should be mentioned that the range of applicability and accuracy of this model is constrained by the data used in the training step. However, the presented model may be applicable in analyzing the ground movements in the other geotechnical conditions and tunneling methods, if the model is trained using the data related to those conditions.

This research utilized the geometrical parameters and stiffness ratio of buildings, settlement trough parameters and relative location of buildings and tunnel to estimate building damage induced by tunneling. The influences of non-linear building behaviour were not considered in simulations. Furthermore, the range of applicability and accuracy of the presented model to predict potential risk of building damage induced by tunneling is limited by the data used in the training step. However, the model presented can be used to predict building damage induced by all the existing tunneling methods and even braced excavations, while the parameters of the settlement trough and adjacent buildings are available.

1.6 Outline of Thesis

This thesis is composed of eight chapters and six appendices. The summaries of the chapters are as follows:

Chapter 1 presents the background of the study, statement of the problems, research objectives, significant, scope and limitation of the study.

Chapter 2 explains the ground movements associated with tunnel construction and reviews the existing methods for predicting transverse and longitudinal surface settlements due to tunneling. In addition, a number of available methods to estimate potential risk of building damage induced by ground movements due to tunneling are reviewed.

Chapter 3 explains the fundamental concepts and various types of artificial neural networks. The learning process by means of backpropagation algorithm is also describes in this chapter. In addition, the concepts, parameters and procedure of particle swarm optimization algorithm are also introduced.

Chapter 4 describes the methodology of the research. The framework of the research is presented and procedure of the modeling is explained.

Chapter 5 presents general descriptions of the KUR project as the case study in this research. The geological and geotechnical conditions, tunneling method and monitoring program of this project are described in this chapter.

Chapter 6 gives the analysis on the effects of influential geotechnical and tunneling parameters on maximum surface settlement associated with NATM tunneling. Subsequently, a hybrid artificial neural network and particle swarm optimization were introduced in order to predict transverse and longitudinal surface settlement troughs caused by tunneling. A computer code is developed and an optimal model is introduced based on sensitivity analyses to predict tunneling-induced ground movements.

Chapter 7 presents a new method based on hybrid artificial neural network and particle swarm optimization to simulate building damages induced by ground movements due to tunneling. In this chapter verification and validation are

performed by comparing the obtained results of proposed method with the results obtained by deep beam theory and actual values obtained from field monitoring.

Chapter 8 contains the conclusion of the research, the contributions made and some recommendations for future works.

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