STREAMFLOW MODELING OF A LARGE ARID CATCHMENT USING SEMI-DISTRIBUTED HYDROLOGICAL MODEL AND MODULAR NEURAL NETWORK

MILAD JAJARMIZADEH

UNIVERSITI TEKNOLOGI MALAYSIA
STREAMFLOW MODELING OF A LARGE ARID CATCHMENT USING SEMI-DISTRIBUTED HYDROLOGICAL MODEL AND MODULAR NEURAL NETWORK

MILAD JAJARMIZADEH

A thesis submitted in fulfilment of the requirements for the award of the degree of Doctor of Philosophy (Civil Engineering)

Faculty of Civil Engineering
Universiti Teknologi Malaysia

OCTOBER 2013
ACKNOWLEDGEMENT

I wish to express my sincere appreciation to my main thesis supervisor, Associate Professor Dr. Sobri Harun from Faculty of Civil Engineering, UTM, for all the invaluable excellent guidance, technical support, encouragement, concern, critics, advices and friendship.

I appreciate the cooperation and help given by the Department of Hydraulic and Hydrology, Centre of Information and Communication Technology (CICT) of Universiti Teknologi Malaysia, consultant engineers of Ab Rah Saz Shargh Corporation in Iran, and the Regional Water Organization, Agricultural Organization, and Natural Resources Organization of the Hormozgan province, Iran.

Last but not least, I am deeply grateful to my lovely family members for their unconditional supports and encouragements from the beginning of this project until the end. I dedicate this research to my beloved family specially my mother and my father. Thanks.
Calibration and validation of hydrological models for simulating stream flow can usually be a promising procedure for future sustainable watershed development. Therefore, development of hydrological models with attributed capabilities is vital to explore the models. Recently, arid climate regions are facing critical water resource problems due to elevated water scarcity. The main objective of this research is to compare the Soil and Water Assessment Tool (SWAT), a knowledge driven by semi-distributed hydrological model, with the Modular Neural Network (MNN), a data driven technique, in predicting the daily flow in arid and large scale. Development of SWAT required digital elevation map, hydro-meteorological data, land use map, and soil maps; whilst, the MNN only needed hydro-meteorological data. For both models, a sensitivity analysis that included both calibration and validation with individual uncertainty evaluation methods was carried out. Generally, results for relative errors such as Nash-Sutcliffe, coefficient of determination and percent of bias favored the SWAT for the validation period. Not only that, the absolute error criteria such as root mean square error, mean square error and mean relative error obtained were close to zero for the SWAT as well within the same period. The mean absolute error for both models was similar during the validation period. Results of the uncertainty evaluation were in satisfactory range. Both models had given similar trend for flow prediction during the validation period. Results of box plot, according to 50% (median) of daily flow, showed that both models had respectively overestimated (MNN) and underestimated (SWAT) the daily flow during validation period. Evaluation on runoff volume for each year showed that both models had a one-year underestimation and three-year overestimation in the same period. However, the overestimation of MNN was more obvious. As a conclusion, this study showed that both models have promising prediction performance for daily flow in a large scale watershed with arid climate.
ABSTRAK

### TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>CHAPTER</th>
<th>TITLE</th>
<th>PAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>DECLARATION</td>
<td></td>
<td>ii</td>
</tr>
<tr>
<td>ACKNOWLEDGEMENT</td>
<td></td>
<td>iii</td>
</tr>
<tr>
<td>ABSTRACT</td>
<td></td>
<td>iv</td>
</tr>
<tr>
<td>ABSTRAK</td>
<td></td>
<td>v</td>
</tr>
<tr>
<td>TABLE OF CONTENTS</td>
<td></td>
<td>vi</td>
</tr>
<tr>
<td>LIST OF TABLES</td>
<td></td>
<td>xii</td>
</tr>
<tr>
<td>LIST OF FIGURES</td>
<td></td>
<td>xv</td>
</tr>
<tr>
<td>LIST OF SYMBOLS</td>
<td></td>
<td>xxii</td>
</tr>
<tr>
<td>LIST OF APPENDICES</td>
<td></td>
<td>xxxi</td>
</tr>
</tbody>
</table>

1  INTRODUCTION  1

1.1 Background of the Study  1
1.2 Statement of Problem  4
1.3 Justification and Significance of Research  6
1.4 Study Objectives  8
1.5 Scope of the Study  9
1.6 Structure of the Thesis  10

2  LITERATURE REVIEW  11

2.1 Introduction  11
2.2 Hydrological Processes and Water Resources  11
    2.2.1 Hydrological Process in Watershed  13
    2.2.2 Runoff  14
    2.2.3 Water Resources and Arid Regions  14
2.2.3.1 Drought and Flood 15
2.2.3.2 Water Pollution 16
2.2.3.3 Importance of Water Crisis in Arid And Semi Arid Regions 18

2.3 Hydrological modeling 20
2.3.1 Hydrological Models 21
   2.3.1.1 Black Box models 22
   2.3.1.2 Deterministic Models 23
   2.3.1.3 Conceptual Models 23
2.3.2 Building Hydrological Model 25
   2.3.2.1 Sensitivity Analysis 26
   2.3.2.2 Model Calibration and Validation 26
   2.3.2.3 Uncertainty Analysis 27
2.3.3 Development and Application of Hydrological models 28

2.4 Semi-Distributed Hydrological Model 31
2.4.1 Theoretical Consideration for SWAT Model 34
   2.4.1.1 Land Phase 34
   2.4.1.2 Climate 35
   2.4.1.3 Hydrology 35
   2.4.1.4 Land Cover 37
   2.4.1.5 Erosion 37
   2.4.1.6 Nutrients and pesticides 38
   2.4.1.7 Management 38
   2.4.1.8 Routing Phase 39
2.4.2 Sequential Uncertainty Fitting (SUFI-2) Calibration Procedure 40
2.4.3 Development and Application of SWAT model 42

2.5 Artificial Neural Networks 46
2.5.1 Biological Neuron and Artificial Neuron 47
   2.5.1.1 Structure and Architecture of ANNs 49
   2.5.1.2 Classifying the Networks 51
2.5.2 Type of Neural Networks 52
   2.5.2.1 Multilayer Perceptrons Network (MLP) 52
2.5.2.2 Generalized Feed Forward Network (GFF) 53
2.5.2.3 Modular Neural Networks (MNN) 53
2.5.2.4 Radial Basis Function Networks (RBF) 54
2.5.2.5 Self Organize Feature Map Networks (SOFM) 54
2.5.2.6 Support Vector Machine Networks (SVM) 54
2.5.3 Building Neural Networks Models 55
   2.5.3.1 Transfer Function 55
   2.5.3.2 Training (Calibration) of ANN 55
   2.5.3.3 Test (Validation) of ANN 57
   2.5.3.4 Training Algorithms 58
   2.5.3.5 Predictive Uncertainty in Neural Networks (PU) 59
2.5.4 Development and Application of ANNs 60
2.6 Summary of Literature Review 64

3 METHODOLOGY 67
3.1 Introduction 67
3.2 General Introduction of Iran 69
3.3 Study Area
   3.3.1 Soil Features 76
   3.3.2 Land Use Features 79
   3.3.3 Meteorological Stations 80
3.4 Data Analysis
   3.4.1 Precipitation 83
   3.4.2 Temperature 87
   3.4.3 Stream Flow Evaluation 89
3.5 Modeling Stream Flow by SWAT 90
   3.5.1 Digital Elevation Map (DEM) 90
   3.5.2 Digital Stream Networks 94
   3.5.3 Land Use Map 95
   3.5.4 Land Use Update File (Lup.Dat) 96
   3.5.5 Land Use Map Roodan 96
   3.5.6 Soil Map 100
3.5.7 Slope Classification and HRU definition 103
3.5.8 Weather Stations and River Discharge Gauge 106
3.5.9 Potential Evapotranspiration Calculation Using SWAT 107
3.5.10 Governing Equations for Calculation of Stream Flow by SWAT 108
3.5.11 Governing Equations for Water Routing Using SWAT 114
3.5.12 Model Set Up For Roodan Watershed 117
3.5.13 Sensitivity Analysis of SWAT model 119
3.5.14 Calibration and Validation of SWAT Model By SUFI-2 Algorithm 122

3.6 Modeling Stream Flow by Modular Neural Network 125

3.7 General Algorithm of Modular Neural Network (MNN) development 125
  3.7.1 Data collection 126
  3.7.2 Identification of predictors 126
  3.7.3 Data Preprocessing (Stage 1) 128
  3.7.4 Network Selection: Modular Neural Network (MNN) 129
    3.7.4.1 Introduction of Modular Neural Network (MNN) 129
    3.7.4.2 Components of Every Module (Neural Expert) For MNN 131
    3.7.4.3 Transfer Function 131
    3.7.4.4 Learning Rule and Training Algorithm 134
  3.7.5 Data Preprocessing (Stage 2) 137
  3.7.6 Network Architecture (Topology) and Training 139
  3.7.7 Evaluation Developed Model 142
  3.7.8 Development of MNN For Roodan Watershed 142
  3.7.9 Predictive Uncertainty In Neural Networks (PU) 147

3.8 Estimation Error Criteria and Model Performance Assessment 147
3.9 Summary 151

4 RESULTS AND DISCUSSION 152

4.1 Introduction 152

4.2 Soil and Water Assessment Tool Result:

   Sensitivity Analysis 152

   4.2.1 Optimum Calibration Scheme For SWAT Model 168

   4.2.2 Results of Calibration and Validation of SWAT Model (Scheme 3) 169

   4.2.3 Calibration and Validation Results 170

   4.2.4 Graphical Comparisons and Statistical Indices For Residual Error 175

   4.2.5 Evaluation daily runoff volume by SWAT 189

4.3 Modular Neural Network Results:

   Sensitivity Analysis 192

   4.3.1 Optimum Developed Architecture for MNN 196

   4.3.2 Predictive Uncertainty and Primary Evaluation Developed MNN 199

   4.3.3 Calibration(Train) and Validation(Test) Results 201

   4.3.4 Graphical Comparisons and Statistical Indices for Residuals Error 206

   4.3.5 Evaluation Daily Runoff Volume by MNN 218

4.4 Assessment of Stream Flow Modeling By SWAT Versus MNN 221

   4.4.1 Residual Error Evaluation for SWAT Versus MNN 228

4.5 Evaluation of Runoff Volume for SWAT Versus MNN 238

4.6 A Discussion on Comparison of SWAT Versus MNN 241

4.7 Advantages and Disadvantages of SWAT and MNN 243
5 CONCLUSION AND RECOMMENDATION

5.1 Introduction 246
5.2 Conclusion for Semi-Distributed Hydrological Model 247
5.3 Conclusion for Modular Neural Network 249
5.4 Conclusion for Semi-Distributed Hydrological Model Versus Modular Neural Network 251
5.5 Contribution of Study 254
5.6 Recommendation for Future Research 254

REFERENCES 256

Appendices A-L 273-296
# LIST OF TABLES

<table>
<thead>
<tr>
<th>TABLE NO.</th>
<th>TITLE</th>
<th>PAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1</td>
<td>Training algorithm guidance for application (Anderson and McNeill, 1992)</td>
<td>59</td>
</tr>
<tr>
<td>3.1</td>
<td>Physiographic features of Roodan watershed and attributed sub-basins</td>
<td>74</td>
</tr>
<tr>
<td>3.2</td>
<td>Specification of meteorological stations used for Roodan study</td>
<td>81</td>
</tr>
<tr>
<td>3.3</td>
<td>Coefficient of correlation between daily maximum temperature for Roodan watershed’s stations</td>
<td>88</td>
</tr>
<tr>
<td>3.4</td>
<td>Coefficient of correlation between daily minimum temperature for Roodan watershed’s stations</td>
<td>88</td>
</tr>
<tr>
<td>3.5</td>
<td>Coefficient of correlation between stream flow m$^3$/s (CMS) and precipitation (mm) data for Roodan watershed</td>
<td>90</td>
</tr>
<tr>
<td>3.6</td>
<td>Topographic report of simulated sub-basins for Roodan watershed by SWAT</td>
<td>91</td>
</tr>
<tr>
<td>3.7</td>
<td>Land use coverage and related codes in Roodan watershed by SWAT</td>
<td>98</td>
</tr>
<tr>
<td>3.8</td>
<td>Percentage of alternation of land use in Lup.file 1 for 1988</td>
<td>99</td>
</tr>
<tr>
<td>3.9</td>
<td>Percentage of alternation of land use in Lup.file 2 for 1993</td>
<td>99</td>
</tr>
<tr>
<td>3.10</td>
<td>Percentage of alternation of land use in Lup.file 3 for 2002</td>
<td>99</td>
</tr>
<tr>
<td>3.11</td>
<td>Percentage of alternation of land use in Lup.file 5 for 1988</td>
<td>99</td>
</tr>
<tr>
<td>3.12</td>
<td>Percentage of alternation of land use in Lup.file 6 for 1993</td>
<td>99</td>
</tr>
<tr>
<td>3.13</td>
<td>Percentage of alternation of land use in Lup.file 6 for 2002</td>
<td>100</td>
</tr>
<tr>
<td>3.14</td>
<td>Required essential parameters for each layer soil in SWAT model</td>
<td>100</td>
</tr>
</tbody>
</table>
3.15 Utilized codes in soil map of Roodan watershed 102
3.16 Determination of slope classes for Roodan watershed in SWAT 103
3.17 26 effective parameters on flow prediction using SWAT model 121
3.18 Thiessen polygon’s weights belonging to the meteorological stations in Roodan watershed 127
3.19 Transfer function chosen in developing MNN for Roodan watershed 132
3.20 Training algorithms chosen in developing MNN 135
3.21 Selected developed MNN architectures for Roodan watershed 140
3.22 Selected some combination during the training MNN 144
4.1 Sensitivity analysis of global scheme by SUFI-2 156
4.2 Sensitivity analysis of discretization scheme by SUFI-2 157
4.3 Sensitivity analysis the optimum scheme by SUFI-2 158
4.4 Adjusted values for sensitive parameters in last iteration of SUFI-2 for scheme 3(optimum scheme) 161
4.5 Criteria for examining the accuracy of calibration (1989-2002) for daily flow by SWAT for three schemes 168
4.6 Criteria for examining the accuracy of calibration (1989-2002) and validation (2003-2008) for daily flow 170
4.7 Percentile of absolute error between observed and simulated flow (CMS) 182
4.8 Comparison between observed and simulated flow for the calibration period (1989-2002) 182
4.9 Comparison between observed and simulated flow for the validation period (2003-2008) 183
4.10 Optimum architecture of MNN in Roodan watershed 197
4.11 Criteria for examining the accuracy of calibration (1989-2002) and validation (2003-2008) for daily flow 201
4.12 Percentile of absolute error value between observed and simulated flow (CMS) 212
4.13 Comparison between observed and simulated flow for the calibration period (1989-2002) 213
4.14 Comparison between observed and simulated flow for the validation period (2003-2008)  213
4.16 Percentile of absolute error between observed and simulated flow (CMS) for SWAT and MNN  234
4.17 Comparison between observed and simulated flow (SWAT and MNN) for the calibration period (1989-2002)  234
4.18 Comparison between observed and simulated flow (SWAT and MNN) for the validation period (2003-2008)  234
4.19 Comparison of the maximum simulated flow discharge values by SWAT and MNN models during calibration period  236
4.20 Comparison of the maximum simulated flow discharge values by SWAT and MNN models for validation  236
# LIST OF FIGURES

<table>
<thead>
<tr>
<th>FIGURE NO.</th>
<th>TITLE</th>
<th>PAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>Global distribution of water Scarcity by Oki and Kanae, (2006)</td>
<td>7</td>
</tr>
<tr>
<td>2.1</td>
<td>The hydrological cycle by Chow et al. (1988)</td>
<td>13</td>
</tr>
<tr>
<td>2.2</td>
<td>Mean annual global precipitations between 1980 and 2004 by Pidwirny,(2006)</td>
<td>15</td>
</tr>
<tr>
<td>2.3</td>
<td>Relative changes (ratio) of drought frequency between the end of 21st century and the average of 20th century by Kanae, (2009)</td>
<td>16</td>
</tr>
<tr>
<td>2.4</td>
<td>Water stress indicator around world in 1999 (World water council, 2009)</td>
<td>18</td>
</tr>
<tr>
<td>2.5</td>
<td>Water availability around the world measured in terms of 1000 m³ per capita / year (Balon and Dehnad, 2006)</td>
<td>19</td>
</tr>
<tr>
<td>2.6</td>
<td>Prediction of water distribution around the world in 2025 (Balon and Dehnad,2006)</td>
<td>19</td>
</tr>
<tr>
<td>2.7</td>
<td>Distribution of fresh water use (Balon and Dehnad, 2006)</td>
<td>20</td>
</tr>
<tr>
<td>2.8</td>
<td>Hydrological models classification by Gosain et al. (2009)</td>
<td>22</td>
</tr>
<tr>
<td>2.9</td>
<td>SWAT development history (Gassman et al.,2007)</td>
<td>32</td>
</tr>
<tr>
<td>2.10</td>
<td>Schematic of representation of hydrological cycle in SWAT model (Neitsch et al., 2005)</td>
<td>34</td>
</tr>
<tr>
<td>2.11</td>
<td>Routing process in SWAT model (Neitsch et al., 2005)</td>
<td>39</td>
</tr>
<tr>
<td>2.12</td>
<td>Conceptual illustration of SUFI-2 algorithm for SWAT calibration (Abbaspour et al., 2007)</td>
<td>42</td>
</tr>
<tr>
<td>2.13</td>
<td>A simple biological neuron (Anderson and McNeill, 1992)</td>
<td>48</td>
</tr>
<tr>
<td>2.14</td>
<td>A basic artificial neuron by Anderson and McNeill,(1992)</td>
<td>49</td>
</tr>
</tbody>
</table>
2.15 Diagram of a simple neural network 50
2.16 Structure of the three-layered feed forward neural network 51
2.17 Structure of the three-layered feedback neural network 52
2.18 General training approaches by ANNs 56
2.19 General classification of training algorithms 57
3.1 General methodology of this research 68
3.2 Water management map of Iran by Faramarzi et al. (2009) 70
3.3 Iran climates classification 72
3.4 Location of Roodan watershed in Iran 73
3.5 Main sub-basins in Roodan watershed
   (Ab Rah Saz Shargh, 2009) 74
3.6 Satellite Image from reservoir of Esteghlal
   (Minab) Dam in 2011 76
3.7 Relative permeability map of Roodan watershed
   (Ab Rah Saz Shargh, 2009) 77
3.8 Geomorphology map of Roodan watershed
   (Ab Rah Saz Shargh, 2009) 78
3.9 Satellite image of land Sat 7 for Roodan watershed (2002) 80
3.10 Whether stations for Roodan watershed 82
3.11 Double mass curve of Dare Shoor station versus other stations 83
3.12 Double mass curve of Zahmakan station
   versus other stations 84
3.13 Double mass curve of Golashgerd station versus other stations 84
3.14 Double mass curve of Madan Asminoon station
   versus other stations 84
3.15 Double mass curve of Bargah station versus other stations 85
3.16 Double mass curve of Bejgan station versus other stations 85
3.17 Double mass curve of Bolbol Abad station versus other stations 85
3.18 Double mass curve of Barantin station versus other stations 86
3.19 Double mass curve of Faryab station versus other stations 86
3.20 Double mass curve of Meshkaldin station versus other stations 86
3.21 Double mass curve of Sargero station versus other stations 87
3.22 Trend analysis temperature data for Roodan watershed 88
3.23 Trend analysis daily precipitation (mm) and stream flow m³/s
3.24 Digital elevation model of Roodan by SWAT
3.25 Digital river networks and outlets of the watershed
3.26 Land use map Roodan watershed in SWAT
3.27 Utilized soil map of Roodan watershed
3.28 Slope classes in Roodan watershed by SWAT
3.29 Sub-basins and all HRUs (full HRU) in Roodan watershed
3.30 Relationship rainfall with runoff in SCS-CN method by Neitsch et al. (2005)
3.31 Final setup SWAT due to run the developed model
3.32 General steps of ANN development by Dawson and Wilby, (2001)
3.33 Distribution Thiessen polygon for meteorological stations in Roodan watershed
3.34 General diagrammatic of modular feed forward network
3.35 General diagrammatic of training versus cross validation
4.1 SUFI-2 results for the global scheme (Vertical axis: value of Nash-Sutcliffe; Horizontal axis: value of parameter)
4.2 SUFI-2 results for the discretization scheme (Vertical axis: value of Nash-Sutcliffe; Horizontal axis: value of parameter)
4.3 SUFI-2 results for the optimum scheme (Vertical axis: value of Nash-Sutcliffe; Horizontal axis: value of parameter)
4.4 Measured and simulated stream flow (CMS) over calibration (1989-2002)
4.5 Measured and simulated stream flow (CMS) over validation (2003-2008)
4.6 Cumulative daily stream flow m³/s (CMS)
for calibration period

4. 7 Cumulative daily stream flow m$^3$/s (CMS) for validation period

4.8 Scatter plot of observed and simulated flows m$^3$/s (CMS) for calibration (1989-2003)

4.9 Scatter plot of observed and simulated flows m$^3$/s (CMS) for validation period (2003-2008)

4.10 Residual error trend analysis for daily stream flow (CMS) over calibration period

4.11 Residual error trend analysis for stream flow (CMS) over the validation period

4.12 Residual error plot (observed minus simulated) against observed flows for calibration

4.13 Residual error plot (observed minus simulated) against observed flows for validation

4.14 Box plot of observed (left hand) and simulated (right hand) daily flow m$^3$/s (CMS) over the calibration period (1989-2002)

4.15 Box plot of observed (left hand) and simulated (right hand) daily flow m$^3$/s (CMS) over the validation period (2003-2008)

4.16 Daily observed flow m$^3$/s (CMS) and precipitation (mm) in the Roodan watershed during calibration

4.17 Daily simulated flow m$^3$/s (CMS) and precipitation (mm) in the Roodan watershed during calibration

4.18 Daily observed flow m$^3$/s (CMS) and precipitation (mm) in the Roodan watershed during validation

4.19 Daily simulated flow m$^3$/s (CMS) and precipitation (mm) in the Roodan watershed during validation

4.20 Doughnut chart ratio of observed against simulated data for total daily runoff volume (m$^3$) in calibration by SWAT

4.21 Doughnut chart ratio of observed against simulated for total daily runoff volume (m$^3$) in validation by SWAT

4.22 Total daily runoff volume calculated by SCS-CN method using SWAT for each year separately over calibration period
4.23 Total daily runoff volume calculated by SCS-CN method using SWAT for each year separately over validation period 191
4.24 Sensitivity of precipitation (PCP) on discharge simulation 194
4.25 Sensitivity of flow (Q) on discharge simulation 194
4.26 Sensitivity of temperature (TMP) on discharge simulation 195
4.27 Impact of combination input variables on discharge 195
4.28 Impact of combination of input variables on discharge 196
4.29 Training and cross validation curves attributed with MSE for MNN 198
4.30 Predictive uncertainty of developed MNN for Roodan watershed 200
4.31 Measured and simulated stream flow (CMS) over calibration period 202
4.32 Measured and simulated stream flow (CMS) over validation period 202
4.33 Cumulative daily stream flow m³/s (CMS) for calibration period 203
4.34 Cumulative daily stream flow m³/s (CMS) for validation period 204
4.35 Scatter plot of observed and simulated flows m³/s (CMS) for the calibration period (1989-2003) 205
4.36 Scatter plot of observed and simulated flows m³/s (CMS) for validation period (2003-2008) 205
4.37 Residual error between observed and simulated flow m³/s (CMS) over the calibration period (1989-2002) 206
4.38 Residual error between observed and simulated flow m³/s (CMS) over the validation period (2003-2008) 207
4.39 Residual error (observed minus simulated) plot against observed flows for the calibration period 208
4.40 Residual error (observed minus simulated) plot against observed flows for the validation period 208
4.41 Box plot of observed (left hand) and simulated (right hand) daily flow m³/s (CMS) over the calibration period (1989-2002) 210
4. 42 Box plot of observed (left hand) and simulated (right hand) daily flow m³/s (CMS) over the validation period (2003-2008)

4.43 Daily observed flow m³/s (CMS) and precipitation (mm) in the Roodan watershed during calibration

4.44 Daily simulated flow m³/s (CMS) and precipitation (mm) in the Roodan watershed during calibration

4.45 Daily observed flow m³/s (CMS) and precipitation (mm) in the Roodan watershed during validation

4.46 Daily simulated flow m³/s (CMS) and precipitation (mm) in the Roodan watershed during validation

4.47 Doughnut chart ratio of observed against simulated data for total daily runoff volume (m³) in calibration by MNN

4.48 Doughnut chart ratio of observed against simulated for total daily runoff volume (m³) in validation by MNN

4.49 Total daily runoff volume derived by MNN model for each year separately over the calibration period

4.50 Total daily runoff volume derived by MNN model for each year separately over the validation period

4.51 Measured and simulated daily stream flow (CMS) over calibration

4.52 Measured and simulated daily stream flow (CMS) over validation

4.53 Measured and simulated daily flow for February 1993

4.54 Measured and simulated daily flow for February 2005

4.55 Cumulative daily stream flow (CMS) for calibration period

4.56 Cumulative daily stream flow (CMS) for validation period

4.57 Scatter plot of observed and simulated flows (CMS) by SWAT (Blue circle) and MNN (Green circle) for calibration (1989-2003)

4.58 Scatter plot of observed and simulated flows (CMS) by SWAT (Blue circle) and MNN (Green circle) for the validation period (2003-2008)

4.59 Residual error of flow (CMS) (observed minus simulated)
for SWAT versus MNN over the calibration period (1989-2002)  228
4.60 Residual error of flow (CMS) (observed minus simulated) for SWAT versus MNN over the validation period (2003-2008)  229
4.61 Box plots of flows m$^3$/s over the calibration period for observed (right) data, SWAT (middle) and MNN (left) models  230
4.62 Box plots of flows m$^3$/s over validation period for observed (right) data, SWAT (middle) and MNN (left) models  232
4.63 Trend of relative error for SWAT and MNN in the calibration period for flows over 1000 CMS  237
4.64 Trend of relative error for SWAT and MNN in the validation period for flows over 500 CMS  237
4.65 Observed flow, and SWAT and MNN simulated flow for total daily runoff volume (m$^3$) for calibration  238
4.66 Observed, SWAT and MNN simulated flow for total daily runoff volume (m$^3$) in validation  239
4.67 Total daily runoff volume derived from MNN and SWAT for each year over the calibration period  240
4.68 Total daily runoff volume derived from MNN and SWAT for each year over the validation period  240
4.69 General pros and cons of the SWAT and MNN model  245
<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alpha_Bf</td>
<td>Base flow alfa factor (days)</td>
</tr>
<tr>
<td>ANFIZ</td>
<td>Adaptive neuron fuzzy inference system</td>
</tr>
<tr>
<td>ANN</td>
<td>Artificial Neural Network</td>
</tr>
<tr>
<td>Biomix</td>
<td>Biological mixing efficiency</td>
</tr>
<tr>
<td>Blai</td>
<td>Maximum potential leaf area index</td>
</tr>
<tr>
<td>BPA</td>
<td>Back propagation algorithm</td>
</tr>
<tr>
<td>BPMA</td>
<td>Back propagation with momentum algorithm</td>
</tr>
<tr>
<td>bsn</td>
<td>Basin files</td>
</tr>
<tr>
<td>Canmx</td>
<td>Maximum canopy storage (mm)</td>
</tr>
<tr>
<td>CGA</td>
<td>Conjugate Gradient Algorithm</td>
</tr>
<tr>
<td>CGCM</td>
<td>Canadian Global Coupled Model</td>
</tr>
<tr>
<td>Ch_K2</td>
<td>Effective hydraulic conductivity in main channel (mm/hr)</td>
</tr>
<tr>
<td>Ch_N2</td>
<td>Manning's &quot;n&quot; value for the main channel</td>
</tr>
<tr>
<td>CLAY</td>
<td>Clay content</td>
</tr>
<tr>
<td>CMS</td>
<td>Cubic meter per second</td>
</tr>
<tr>
<td>CN</td>
<td>Curve number</td>
</tr>
<tr>
<td>Cn2</td>
<td>Initial SCS runoff curve number for moisture condition II</td>
</tr>
<tr>
<td>CRIR</td>
<td>Agricultural area</td>
</tr>
<tr>
<td>CUP</td>
<td>Calibration and uncertainty procedures</td>
</tr>
<tr>
<td>DEM</td>
<td>Digital elevation map</td>
</tr>
<tr>
<td>div</td>
<td>Volume of water added or removed from the reach for the day through diversions (m³)</td>
</tr>
<tr>
<td>EPCO</td>
<td>Plant uptake compensation factor</td>
</tr>
<tr>
<td>ESCO</td>
<td>Soil evaporation compensation factor</td>
</tr>
<tr>
<td>EVRCH.bsn</td>
<td>Reach evaporation coefficient</td>
</tr>
<tr>
<td>Ext</td>
<td>SWAT file extension</td>
</tr>
<tr>
<td>FAO</td>
<td>Food and agriculture organization</td>
</tr>
<tr>
<td>FFNN</td>
<td>Feed Forward Neural Networks</td>
</tr>
<tr>
<td>GA</td>
<td>Genetic Algorithm</td>
</tr>
<tr>
<td>GB</td>
<td>Giga bites</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Description</td>
</tr>
<tr>
<td>--------------</td>
<td>-------------</td>
</tr>
<tr>
<td>GFF</td>
<td>Generalized Feed Forward</td>
</tr>
<tr>
<td>GHz</td>
<td>Giga hertz</td>
</tr>
<tr>
<td>GIS</td>
<td>Geographic Information System</td>
</tr>
<tr>
<td>GLUE</td>
<td>Generalized Likelihood Uncertainty Estimation</td>
</tr>
<tr>
<td>GRU</td>
<td>Grouped Response Unit</td>
</tr>
<tr>
<td>gw</td>
<td>Ground water files</td>
</tr>
<tr>
<td>Gw_Delay</td>
<td>Groundwater delay time (days)</td>
</tr>
<tr>
<td>Gwqmn</td>
<td>Threshold depth of water in the shallow aquifer (mm)</td>
</tr>
<tr>
<td>Gw_Revap</td>
<td>Groundwater &quot;revap&quot; coefficient</td>
</tr>
<tr>
<td>HRU</td>
<td>Hydrological Response Unit</td>
</tr>
<tr>
<td>HRU-FR</td>
<td>Hydrological response unit fraction</td>
</tr>
<tr>
<td>hh:mm</td>
<td>Hour-Minute</td>
</tr>
<tr>
<td>hr</td>
<td>Hour</td>
</tr>
<tr>
<td>Hydrogrp</td>
<td>Soil hydrological group</td>
</tr>
<tr>
<td>HYMO</td>
<td>Hydrologic Model</td>
</tr>
<tr>
<td>i</td>
<td>Intensity of precipitation</td>
</tr>
<tr>
<td>IM</td>
<td>Inverse model</td>
</tr>
<tr>
<td>IRIMO</td>
<td>Meteorological Organization of Iran</td>
</tr>
<tr>
<td>j</td>
<td>Input Neuron</td>
</tr>
<tr>
<td>k</td>
<td>Hidden neuron</td>
</tr>
<tr>
<td>k</td>
<td>Number of observed data</td>
</tr>
<tr>
<td>km²</td>
<td>Square Kilometer</td>
</tr>
<tr>
<td>l</td>
<td>Output neuron</td>
</tr>
<tr>
<td>L</td>
<td>Channel length (km)</td>
</tr>
<tr>
<td>LH-OAT</td>
<td>Latin hypercube sampling by one at a time design</td>
</tr>
<tr>
<td>LMA</td>
<td>Levenberg-Marquardt algorithm</td>
</tr>
<tr>
<td>Lup.file</td>
<td>Land use update file</td>
</tr>
<tr>
<td>M</td>
<td>Total number of observations</td>
</tr>
<tr>
<td>m</td>
<td>Parameters</td>
</tr>
<tr>
<td>MAE</td>
<td>Mean Absolute Error</td>
</tr>
<tr>
<td>Max Temp</td>
<td>Average daily maximum temperature</td>
</tr>
<tr>
<td>mgt</td>
<td>Management file</td>
</tr>
<tr>
<td>MIGS</td>
<td>Mix grassland/shrub land</td>
</tr>
<tr>
<td>Min Temp</td>
<td>Average daily minimum temperature</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Description</td>
</tr>
<tr>
<td>--------------</td>
<td>-------------</td>
</tr>
<tr>
<td>MLP</td>
<td>Multilayer Perceptron</td>
</tr>
<tr>
<td>MLR</td>
<td>Multiple linear regression</td>
</tr>
<tr>
<td>MNN</td>
<td>Modular Neural Network</td>
</tr>
<tr>
<td>MNN1..14</td>
<td>Developed MNN architectures number</td>
</tr>
<tr>
<td>MRE</td>
<td>Mean Relative Error</td>
</tr>
<tr>
<td>M-RBF-NN</td>
<td>Modular Radial Basis Function Neural Network</td>
</tr>
<tr>
<td>MSE</td>
<td>Mean Squared Error</td>
</tr>
<tr>
<td>N</td>
<td>Number of interval</td>
</tr>
<tr>
<td>n</td>
<td>Total number of observations</td>
</tr>
<tr>
<td>n</td>
<td>Number of time steps</td>
</tr>
<tr>
<td>n</td>
<td>Total number of measured data</td>
</tr>
<tr>
<td>n</td>
<td>Iteration</td>
</tr>
<tr>
<td>n</td>
<td>Number of lags</td>
</tr>
<tr>
<td>NRCS-CN</td>
<td>Natural Resources Conservation Services Curve Number</td>
</tr>
<tr>
<td>N S</td>
<td>Nash-Sutcliffe</td>
</tr>
<tr>
<td>ORCD</td>
<td>Orchard</td>
</tr>
<tr>
<td>Paraname</td>
<td>Name of parameter in SWAT</td>
</tr>
<tr>
<td>ParaSol</td>
<td>Parameter Solution</td>
</tr>
<tr>
<td>PBIAS</td>
<td>Percentage of bias</td>
</tr>
<tr>
<td>PCP</td>
<td>Precipitation (mm)</td>
</tr>
<tr>
<td>PCPD</td>
<td>Average number of days of precipitation in month</td>
</tr>
<tr>
<td>PCPMM</td>
<td>Average total monthly precipitation (mm)</td>
</tr>
<tr>
<td>PCPSKW</td>
<td>Skew coefficient for daily precipitation in month</td>
</tr>
<tr>
<td>PCPSTD</td>
<td>Standard deviation for daily precipitation in month (mm/day)</td>
</tr>
<tr>
<td>PE</td>
<td>Process Element</td>
</tr>
<tr>
<td>PET</td>
<td>Potential Evapotranspiration (mm/day)</td>
</tr>
<tr>
<td>PLS</td>
<td>Partial Least Square</td>
</tr>
<tr>
<td>PPU</td>
<td>Percent Prediction Uncertainty</td>
</tr>
<tr>
<td>PR_W(1)</td>
<td>Probability of a wet day following a dry day in the month</td>
</tr>
<tr>
<td>PR_W(2)</td>
<td>Probability of a wet day following a wet day in the month</td>
</tr>
<tr>
<td>PU</td>
<td>Predictive uncertainty index</td>
</tr>
<tr>
<td>Q</td>
<td>Discharge (m$^3$/s)</td>
</tr>
<tr>
<td>r</td>
<td>Parameter value is multiplied by (1 + a given value) or relative change</td>
</tr>
<tr>
<td>Code</td>
<td>Description</td>
</tr>
<tr>
<td>----------</td>
<td>-----------------------------------------------------------------------------</td>
</tr>
<tr>
<td>RAINHMX</td>
<td>Maximum 0.5 hour rainfall in entire period of record for Month</td>
</tr>
<tr>
<td>RAM</td>
<td>Random access memory</td>
</tr>
<tr>
<td>RBF</td>
<td>Radial Basis Function Network</td>
</tr>
<tr>
<td>RCHRG_DP</td>
<td>Ground water recharge to deep aquifer</td>
</tr>
<tr>
<td>REA</td>
<td>Representative Elementary Area</td>
</tr>
<tr>
<td>Revapmn</td>
<td>Threshold depth of water in the shallow aquifer for percolation to the deep aquifer (mm)</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root Mean Square Error</td>
</tr>
<tr>
<td>ROCK</td>
<td>Rock fragment content</td>
</tr>
<tr>
<td>ROTO</td>
<td>Routing outputs to outlet</td>
</tr>
<tr>
<td>rte</td>
<td>Routing files</td>
</tr>
<tr>
<td>RR</td>
<td>Rainfall-Runoff</td>
</tr>
<tr>
<td>$S$</td>
<td>Retention parameter (mm)</td>
</tr>
<tr>
<td>SAND</td>
<td>Sand content</td>
</tr>
<tr>
<td>SCS-CN</td>
<td>Natural Resources Conservation Service Curve Number Method</td>
</tr>
<tr>
<td>SEE</td>
<td>Unbiased standard error</td>
</tr>
<tr>
<td>Sftmp</td>
<td>Snowfall temperature (°C)</td>
</tr>
<tr>
<td>SHRB</td>
<td>Shrub land</td>
</tr>
<tr>
<td>SILT</td>
<td>Silt content</td>
</tr>
<tr>
<td>Slsubbsn</td>
<td>Average slope length (m)</td>
</tr>
<tr>
<td>Slope</td>
<td>Average slope steepness (m/m)</td>
</tr>
<tr>
<td>Smfmmn</td>
<td>Melt factor for snow on December 21 (mm/°C-day).</td>
</tr>
<tr>
<td>Smfmx</td>
<td>Melt factor for snow on June 21 (mm/°C-day).</td>
</tr>
<tr>
<td>SMMN</td>
<td>Spiking Modular Neural Networks</td>
</tr>
<tr>
<td>Sntmp</td>
<td>Snow melt base temperature (°C).</td>
</tr>
<tr>
<td>SOFM</td>
<td>Self Organize Feature Map Network</td>
</tr>
<tr>
<td>sol</td>
<td>Soil files</td>
</tr>
<tr>
<td>soltext</td>
<td>Soil texture</td>
</tr>
<tr>
<td>Sol_Alb</td>
<td>Moist soil albedo</td>
</tr>
<tr>
<td>SOL_AWC</td>
<td>Available water capacity of the soil layer (mm/mm)</td>
</tr>
<tr>
<td>SOL_BD</td>
<td>Moist bulk density (g/cm$^3$)</td>
</tr>
<tr>
<td>SOL_CBN</td>
<td>Organic carbon content (% soil weight)</td>
</tr>
<tr>
<td>SOL_CRK</td>
<td>Potential or maximum crack volume of the soil profile (m$^3$/m$^3$)</td>
</tr>
<tr>
<td>SOL_EC</td>
<td>Electrical conductivity(ds/m)</td>
</tr>
<tr>
<td>Acronym</td>
<td>Description</td>
</tr>
<tr>
<td>----------</td>
<td>------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>SOL_K</td>
<td>Saturated hydraulic conductivity (mm/hr)</td>
</tr>
<tr>
<td>Sol_Z</td>
<td>Depth from soil surface to bottom of layer (cm)</td>
</tr>
<tr>
<td>SOM</td>
<td>Self-organizing map</td>
</tr>
<tr>
<td>SSA</td>
<td>Singular Spectrum Analysis</td>
</tr>
<tr>
<td>STD</td>
<td>Standard deviation of observed values</td>
</tr>
<tr>
<td>subbsn</td>
<td>Sub-basin number</td>
</tr>
<tr>
<td>SUFI-2</td>
<td>Sequential Uncertainty Fitting-2</td>
</tr>
<tr>
<td>Surlag</td>
<td>Surface runoff lag coefficient</td>
</tr>
<tr>
<td>SVM</td>
<td>Support Vector Machine Network</td>
</tr>
<tr>
<td>SW</td>
<td>Soil water content of the entire profile excluding the amount of water held</td>
</tr>
<tr>
<td>SWAT</td>
<td>Soil and Water Assessment Tool</td>
</tr>
<tr>
<td>Tanh</td>
<td>Tangent hyperbolic</td>
</tr>
<tr>
<td>Temp</td>
<td>Average daily temperature (°C)</td>
</tr>
<tr>
<td>Timp</td>
<td>Snow pack temperature lag factor</td>
</tr>
<tr>
<td>Tlaps</td>
<td>Temperature lapse rate (°C/km)</td>
</tr>
<tr>
<td>tloss</td>
<td>Volume of water lost from the reach by transmission through the bed (m³)</td>
</tr>
<tr>
<td>TMP</td>
<td>Temperature (°C)</td>
</tr>
<tr>
<td>TMPMN</td>
<td>Average daily minimum air temperature for month (°C)</td>
</tr>
<tr>
<td>TMPMX</td>
<td>Average daily maximum air temperature for month (°C)</td>
</tr>
<tr>
<td>TMPSTDMN</td>
<td>Standard deviation for daily minimum air temperature in month (°C)</td>
</tr>
<tr>
<td>TMPSTDMX</td>
<td>Standard deviation for daily maximum air temperature in month (°C)</td>
</tr>
<tr>
<td>TT</td>
<td>Travel time (hour)</td>
</tr>
<tr>
<td>t</td>
<td>Time (days)</td>
</tr>
<tr>
<td>t-1,t-2,…(t-n)</td>
<td>One day before present day</td>
</tr>
<tr>
<td>USDA-ARS</td>
<td>US Department of Agriculture, Agricultural Research Service</td>
</tr>
<tr>
<td>USLE_K</td>
<td>USLE equation soil erosion factor (K)</td>
</tr>
<tr>
<td>URLD</td>
<td>Residential-low density</td>
</tr>
<tr>
<td>URMD</td>
<td>Residential-medium density</td>
</tr>
<tr>
<td>v</td>
<td>Parameter value is replaced by given value or absolute change</td>
</tr>
<tr>
<td>W</td>
<td>Channel width at water level (m)</td>
</tr>
</tbody>
</table>
W(n) - Weight (free parameter)
WGN - Weather Generator File
x - Type of adjustment parameter in SWAT
X(n) - Input variable
α - Momentum
η - Step size
ν - Degrees of freedom
λ - Latent heat of vaporization (MJ kg⁻¹)
β - Line Slope
σ_X - Standard deviation of the measured variable
ν_{ov} - The overland flow velocity (m/s)
δ_i(n) - Local error
ΔV_{stored} - Volume of storage (m³)
R² - Coefficient of determination
Y_{obs} - Measured values at time step i
Y_{sim} - Measured values at time step i
a_x - Regression intercept for a channel
α_{tc} - Fraction of daily rainfall that occurs during the time of concentration
b_k - Bias of the hidden layer
b_l - Bias of the output layer
b_x - Regression slope for a channel
b_{nk}^{in} - Amount of water entering bank storage (m³)
coef_{ev} - Evaporation coefficient
CN_1 - Moisture condition I
CN_2 - Moisture condition II
CN_3 - Moisture condition III
D_i(n) - Desired response to observed output
d_x - Average distance between the upper and the lower 95PPU
E_{ai} - The amount of evapotranspiration on day i (mm)
E_{ei} - The evaporation from the reach for the day (m³)
E_{i}(n) - Error system
E_o - Potential evapotranspiration (mm d⁻¹)
E_{Relative} - Relative Error
$fr_{At}$ - Fraction of the time step in which water is flowing in the channel

$fr_{trns}$ - Fraction of transmission losses partitioned to the deep aquifer

$H_0$ - Extraterrestrial radiation (MJ m$^{-2}$ d$^{-1}$)

$I_a$ - Initial abstractions (mm)

$K_{ch}$ - Effectiveness of hydraulic conductivity for channel alluvium (mm/hr)

$L_{ch}$ - Channel length (m)

$L_{slp}$ - Sub-basin slope length (m)

$O_i$ - Measured value at time $i$

$P_{ch}$ - The wetted perimeter (m)

$P_i$ - Estimated value at time $i$

$P_{max}$ - Maximum observed data

$P_{min}$ - Minimum observed data

$P_n$ - Scaled data

$P_o$ - Observed data

$PCP_t$ - Precipitation (mm) with attributed lags (day)

$Q_{avg}$ - Average observed stream flow

$Q_{sw}$ - Amount of return flow on day $i$ (mm)

$Q_o$ - Observed value of flow

$Q_{obs}$ - Observed value at time $i$

$Q_{obsavg}$ - Average of observed values

$q_{out}$ - Discharge rate (m$^3$/s)

$Q_p$ - Predicted value of flow

$q_{peak}$ - Peak runoff rate (m$^3$ s$^{-1}$)

$Q_{sim}$ - Predicted value at time $i$

$Q_{simavg}$ - Average of predicted values $Q_{stor,i-1}$ - Surface flow lagged from the previous day (mm)

$Q_{stor,i-1}$ - Surface flow lagged from the previous day (mm)

$Q_{surf}$ - The amount of surface runoff on day $i$ (mm)

$Q_{surf}$ - Accumulated runoff excess (mm)

$Q'_{surf}$ - Amount of surface flow created in the sub basin on a given day (mm)

$Q_t$ - Discharge (m$^3$/s) with attributed day lags
$Q_{(m, Obs)_i}$ - Maximum values of the actual discharge during $i$ time

$Q_{(m, Sim)_i}$ - Maximum values of simulated discharge during $i$ time

$R_{day}$ - Rainfall depth for the day (mm)

$R_{tc}$ - Amount of precipitation during the time of concentration (mm)

$S_{max}$ - The maximum value the retention parameter (mm)

$SW_i$ - Final soil water content (mm)

$SW_0$ - Initial soil water content on day $i$ (mm)

$T_{av}$ - Mean air temperature for a given day ($°C$).

$t_{ov}$ - Time of concentration for overland flow (hr)

$t_{ch}$ - Time of concentration for channel flow (hr)

$t_{conc}$ - Time of concentration(hour)

$t_{loss}$ - Transmission losses of channel (m$^3$)

$T_{mn}$ - Minimum air temperature for a given day ($°C$)

$T_{mx}$ - Maximum air temperature for a given day ($°C$)

$V_{bnk}$ - The volume of water summed to the river using return flow from bank storage (m$^3$)

$V_{in}$ - The volume of water flowing into the reach during the time step (m$^3$)

$V_{in}$ - Volume of inflow (m$^3$)

$V_{out}$ - Volume of water flowing out of the reach (m$^3$)

$V_{out}$ - Volume of outflow (m$^3$)

$vol_{Qsurf,f}$ - Volume of runoff after transmission losses (m$^3$)

$vol_{Qsurf,i}$ - Volume of runoff prior to transmission losses (m$^3$)

$V_{stored}$ - Storage volume (m$^3$)

$V_{stored,2}$ - Volume of water in the river at the end of the time step (m$^3$)

$V_{stored,1}$ - Volume of water in the reach at the beginning of the time step (m$^3$)

$vol_{thr}$ - Threshold volume for a channel(m$^3$)

$W_i$ - Bias vector

$W_{kj}$ - Weight of the $j^{th}$ input neuron and $k^{th}$ hidden neuron

$W_{lk}$ - Weight between the $k^{th}$ hidden neuron and $l^{th}$ output neuron

$w_{seep}$ - The amount of water entering the vadose zone

$W_1, W_2$ - Shape coefficients
\( X_i^{lin} = \beta x_i \) - Scaled and offset activity inherited from the Linear

\( X_{min} \) - Minimum input range

\( X_{max} \) - Maximum input range

\( X_n \) - Normalized inputs

\( X_L \) - 2.5\(^{th}\) percentiles of the cumulative distribution for each simulated data

\( X_r \) - Original inputs

\( X_U \) - 97.5\(^{th}\) percentiles of the cumulative distribution for each simulated data

\( Y_i(n) \) - Observed output
## LIST OF APPENDICES

<table>
<thead>
<tr>
<th>APPENDIX</th>
<th>TITLE</th>
<th>PAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Land use/soil/ slope distribution output. file by SWAT for Roodan</td>
<td>273</td>
</tr>
<tr>
<td>B</td>
<td>Command codes of SUFI-2 algorithm for calibration and sensitivity analysis in first and last iteration for scheme 1, scheme 2 and scheme 3</td>
<td>275</td>
</tr>
<tr>
<td>C</td>
<td>Percentile analysis for daily flows during calibration and validation periods by SWAT and MNN results</td>
<td>278</td>
</tr>
<tr>
<td>D</td>
<td>Varying behavior of inputs on discharge (output) for optimum architecture on MNN</td>
<td>279</td>
</tr>
<tr>
<td>E</td>
<td>Increasing neurons for sigmoid and 2 neurons fixed for linear sigmoid</td>
<td>281</td>
</tr>
<tr>
<td>F</td>
<td>Increasing neurons for sigmoid and 26 neurons fixed for linear sigmoid</td>
<td>284</td>
</tr>
<tr>
<td>G</td>
<td>Increasing neurons for linear sigmoid and 2 neurons fixed for sigmoid</td>
<td>287</td>
</tr>
<tr>
<td>H</td>
<td>Increasing neurons for linear sigmoid and 26 neurons fixed for sigmoid</td>
<td>290</td>
</tr>
<tr>
<td>K</td>
<td>MSE values for training (1989-1999) and cross validation (2000-2002) data set with attributed epochs for optimum developed architecture via MNN</td>
<td>295</td>
</tr>
<tr>
<td>L</td>
<td>List of publications attributed with this research during 2009-2013</td>
<td>296</td>
</tr>
</tbody>
</table>
CHAPTER 1

INTRODUCTION

1.1 Background of the Study

A hydrologist or water resources project manager/planner may be interested in knowing the total amount of runoff for a watershed during a specified period of time. The reason can be to obtain reliable runoff yield at a catchment to have more confident on the design-attributed parameters such as the storage capacity, height, power generation, release pattern for irrigation, municipal demands and other requirement (Patra, 2008). Recently, runoff prediction has become significant in regions with arid and dry climates. As such, the management, assessment and planning of water resources are important issues in human development, especially in such regions where rainfall and groundwater supply are limited. McIntyre et al. (2009) has reported that there is a serious need to develop our cognition ability in predicting the hydrological responses in arid catchments.

Arid hydrology has recently become an important topic to water resource planners and researches serious in seeking for solutions in arid zones suffering from water resources crisis. Iran, especially the arid southern part of Iran as well as other Middle East countries, have been facing aridity problems. Reports and investigations showed that Iran have suffered from water crisis since 1999, which then pushed the Iranian government to accept foreign aid (Foltz, 2002). Therefore, development of new techniques such as watershed modeling can be helpful to the cognitive management of water resource management and sustainability for future development.
Runoff is one of the controversial and basic parameter in hydrology that has a significant role in a catchment (Alizadeh, 2007). An efficient design of water structures and sustainable development firstly involve a reliable stream flow prediction from the contributing catchment area. The amount of runoff can be derived from a given precipitation, initial moisture, land use, slopes of the catchment, intensity, distribution, and duration of the rainfall (Irawan, 2005). Hence, rainfall-runoff relationship prediction is inevitably a complicated and non-linear procedure (Shakir and Shardra, 2008).

In the 1960s and 1970s, the use of digital computers for hydrological sciences has overcome some complicated computation problems for rainfall-runoff predictions. For instance, the first watershed model was the Stanford Watershed Model, developed in 1966 by Crawford and Linsley (Singh, 1995). Subsequently, another potentially efficient modeling tool was introduced, and has since been widely used in the soil and water management field. Essentially, rainfall-runoff models are important tools for water resource planning, development, and management (Tombul and Ogul, 2006). The principal techniques of hydrological modeling are made up of the two powerful facilities of the digital computer, which are: (i) the ability to carry out vast numbers of iterative calculations, and (ii) the ability to answer ‘yes’ or ‘no’ to specifically designed interrogations (Shaw, 1994). These days, development/application of hydrological models is a controversial topic due to the prediction of hydrological processes (Singh et al., 2012). Nevertheless, the development of different types of hydrological models in recent days is mainly done based on a review on the weaknesses and strengths of these models. One of the important subjects concerns stream flow modeling and is attributed to the discussions on the assessment of predicted peak flows, the capability of the runoff volume prediction, and so on. Therefore, this research is geared towards the evaluation of stream flow modeling by using the attributed and available data in hydro-meteorology, geomorphologic, agricultural and pedology. Two hydrologic models were used in this research, namely semi-distributed hydrological model (Soil and Water Assessment Tool (SWAT)) and modular neural network (MNN) model.
SWAT was developed by the US Department of Agriculture, Agricultural Research Service (USDA-ARS). It is a semi-distributed hydrological model with some major components like surface hydrology, weather, sedimentation, soil temperature, crop growth, nutrients, groundwater, and lateral flow. SWAT is one of the models which can be developed in large scale and un-gauged basins (Xu et al., 2009a). The reason of developing SWAT model is to delineate a catchment of any sizes, especially in large scale. Its scientific association also concerns its application under different environment.

The black-box/data driven techniques describe the relationship between the input (precipitation) and the output (runoff) mathematically. This hydrological model simulates hydrological process without describing or understanding the physical process. Artificial neural networks (ANNs) have been introduced as a black box/data driven models, while modular neural networks are one of the sub-classes of artificial neural networks (Wu and Chau, 2011). The idea of black box/data driven models is based on the estimation of an output by a function from the input, which is similar to the process of biological neuron cell in the brain. Development of modular neural networks, which are sometimes taken as a hybrid model, is gaining popularity for developing rainfall-runoff relationships (Zhang and Govindaraju, 2000), hydrological processes (Parasuraman et al., 2006), and ground water studies (Almasri and Kaluarachchi, 2005). As a summary, modular networks are still in the stage of infancy. Therefore, there is still a need to evaluate modular networks in terms of its development and generalization for hydrological processes. Essentially, its low data collection cost and fast calculation as a sub-class of artificial neural networks can be the two logical reasons for it to become popular among hydrologists.

In this study, the Roodan watershed in the Southern part of Iran has been selected as the study area. The Roodan watershed is one of the largest catchments which is around 10570km$^2$. It has the potential for future agriculture, animal husbandry and sustainable tourism activities. With respect to modeling, no SWAT model has been developed for this watershed, and so does the MNN for daily stream flow prediction. The comparison of semi-distributed hydrological model (SWAT) and neural network (MNN) in arid and large catchment can be important for the
assessment and discussion on their abilities, and their advantages and disadvantages for stream flow modeling.

1.2 Statement of Problem

The statements of problems which have been identified in this research are as follows:

a) With reference to Parida et al. (2006), prediction on rainfall-runoff relationships has become more difficult for an arid catchment due to the complexity involved in the process of transformation from rainfall to runoff. Sen, (2008) reported that arid regions require more surveys because of a shortage in literatures and cognition modeling responses. In recent years, arid regions have suffered from many problems such as water crisis and depletion of underground waters (Al-Damkhi et al., 2009; Kanae, 2009). Therefore, there is a need to model hydrological processes for arid regions for better cognition of complex rainfall-runoff relationships.

b) The major difficulty in the development of hydrological models is the different concepts of these models. The semi-distributed hydrological model (e.g., SWAT) can be a physically-based model which deal with physical concept of catchment. In contrast, a modular network model is a black box/data driven model which only seeks for best generalization of mathematical procedures. Moreover, development of hydrological models is influenced by the complexity of hydrological processes and this issue is more significant for large scale catchments. Therefore, it is necessary to find the advantages and disadvantages of the semi-distributed hydrological model and the black box/data-driven model (e.g., SWAT versus MNN). By applying SWAT and MNN in the same region, it can help in visualizing and identifying the weaknesses and strengths of these two different models.

c) A semi-distributed hydrological model such as SWAT requires large number of input parameters for its calibration. Generally, the parameters adjusted for
calibration are not measured openly in the case study. SWAT model is usually calibrated manually by using the trial-and-error procedure to make a comparison with the data-driven models. Manual calibration provides proficiency by allowing the modeler to have prior knowledge of the catchment being simulated. Clearly, hydrological models such as SWAT require tough manual effort to obtain better results and it is more time-consuming due to the adjustment needed for a large number of parameters. Sometimes, the complicated calibration process may cause uncertainties in the results due to the nature of the model. This concept is increasingly significant for SWAT model (Abbaspour et al., 2009, 2007). As a result, SWAT requires an optimum calibration and uncertainty procedure to allow a comparison with data driven models like MNN. Therefore, there is a need for SWAT calibration using efficient approach to get optimum results. In this study, the sequential uncertainty fitting-2 (SUFI-2) has been integrated for the calibration of SWAT model.

d) An accurate prediction of rainfall-runoff relationship is extremely difficult due to the spatial and temporal variability of watershed characteristics as well as an incomplete understanding of the underlying complex physical processes (Srivastava et al., 2006). In regard to this, the modular neural networks have found another technique for different hydrology subjects (Almasri and Kaluarachchi, 2005). The motivation of modular (hybrid) architecture in rainfall-runoff modeling came from Zhang and Govindaraju, (2000). In general, modularity architectures allow the hydrologist to carry out high order accounting to have more options in solving complex pattern recognition. This is a motivation to the development of modular networks models. Two major difficulties of the development of neural networks such as MNN are overtraining and over parameterization, which have significant roles on the strength of optimum generalization (test). Therefore, there is a need for integrating cross validation technique (early stopping) to avoid overtraining and predictive uncertainty index (PU) to prevent over parameterization of neural networks.
In conclusion, the comparisons and evaluations of SWAT and MNN can be a promising effort in the arid Roodan watershed to explore the capabilities of related models. The development of the aforementioned models offers a fair cognition for the complex rainfall-runoff relations in large scale arid regions.

1.3 Justification and Significance of Research

Water scarcity affects the agriculture and food production (Kanae, 2009). Global warming has been proven to decrease the water availability in arid and semi-arid regions, where major crop are cultivated. The decreasing water supply for agriculture and domestic usage will inevitably threaten arid and semi-arid areas. Oki and Kanae, (2006) has previously showed their geographical distribution of the ratio between water withdrawal and water availability, and this is as presented in Figure 1.1 (the red coloring indicates a high ratio of water scarcity). Alizadeh, (2007) stated that in the coming years, Iran will be a water-stressed country.
By virtue of Rezaitavabeh et al. (2007), one of the logical solutions for water resource management and promotion of sustainable catchment is to invest in the harvest and collection of surface water. To date, watershed models have become a main tool in addressing a wide spectrum of environment and water resource problems (Singh and Frevert, 2006). Thompson et al. (2004) cited that modeling is fast and less expensive for the evaluation of different management strategies, and thus, can help to avoid undesirable outcomes. Until now, researchers are still persisting on testing and evaluating the stream flow modeling via new techniques to improve the models’ efficiency and to explore the pros and cons of these hydrological models.

In terms of hydrology, researchers are now trying to find the advantages and disadvantages of hydrological modeling to optimize the prediction of rainfall-runoff relationships. This is to find out the capability of the models for future studies (Norani et al, 2008). This function gets more important when different types of
hydrological models with various concepts have been established. Therefore, it is essential to identify their strengths and weaknesses. With reference to Boughton (1984), due to the sparseness of hydrological data in arid and semi-arid areas, the values vary in the results of every hydrological investigation done in these regions. Iran suffers from shortage of water because of the arid and semi-arid climatic conditions, and the country only has an average annual rainfall of 250 mm, which is only around one-third of the world’s average rainfall. Nevertheless, this region has the potential to be developed for agricultural purposes and for collecting surface water. Therefore, the development of hydrological models with different concept such as SWAT and MNN can assist in the daily flow prediction for the Roodan region.

In conclusion, this research is significant for the development of the most popular models (SWAT and MNN) using different types of data in arid region. This research focuses on the prediction of daily runoff. The development of SWAT and MNN can assist in the daily stream flow prediction for the Roodan watershed. Also, daily flow prediction is important for optimal management of the availability of water resources in every basin. A comparison between SWAT and MNN can be an opportunity for the evaluation of optimum solutions by modeling the stream flow for future planning and investment efforts. Finally, this project can show the behavior of SWAT and MNN models, as a subsidiary tool for hydrologists, in predicting daily stream flow in large arid region. Last but not least, such study in arid regions can be interesting and valuable since it has substantially different features in comparison with other climates, as reported by Sen, (2008).

1.4 Study Objectives

The aim of this study is to make a comparison on the daily stream flow prediction between the semi-distributed hydrological model, i.e., the soil and water assessment tool (SWAT), and the black-box/data driven model, i.e., modular neural network (MNN). The objectives of this study are as follows:
1. To model the daily rainfall-runoff relationship of a large arid watershed;
2. To calibrate the SWAT based on the sequential uncertainty fitting-2 algorithm;
3. To propose a MMN using cross-validation technique for modeling the rainfall-runoff relationship; and
4. To evaluate the performance of SWAT and MNN in large arid climate.

1.5 Scope of the Study

The present study was undertaken to compare the daily stream flow through two kinds of hydrological models - SWAT and MNN. The scope of this research can be divided into three parts. The first part involves the development of SWAT model for daily stream flow simulation. The required data for SWAT are the digital elevation modeling map (DEM), the hydro-meteorological data (take from year 1988 to 2008), and the soil and land cover maps collected by individual features availability. A sensitivity analysis and a calibration and uncertainty procedure have been employed together with the application of the Latin hypercube sampling by one at a time design (LH-OAT). These are embedded in SWAT version 2009 and the SUFI-2 algorithm can be found in the SWAT-CUP program (version 2009), respectively. Finally, the weaknesses and strengths of the SWAT model are observed and interpreted for the prediction of daily runoff in the large yet arid Roodan watershed in the southern part of Iran.

The second part of this research involves the development of MNN with two modules (neural expert) for rainfall-runoff relationships in Roodan watershed using the hydro-meteorological data from year 1988 to 2008. Such development requires the training with cross validation and test. Basically, a heuristic method has been involved to find the optimum architecture and attributed components such as number of cells, hidden layers, input variables, and coefficients related to the step size and momentum terms. This study includes the evaluation of uncertainty in the MMN using the predictive uncertainty (PU) index.

The third part of this research involves the respective evaluations and comparisons between the daily flow models for the arid and large scale catchment
area through general graphical and non-graphical analyses. This comparison has offered the general features of robustness, accuracy, efficiency, and reliability. This has made it possible to identify and discuss the advantages and disadvantages of SWAT versus MNN for daily flow prediction.

1.6 Structure of the Thesis

This thesis consists of five chapters. The first chapter presents the background, introduction, objectives, and the scope of this research. In the subsequent chapter, a review of relevant literature and theoretical definitions will be illustrated using the hydrological cycle. A discussion will also be put forth in regard to some water resource problems and crisis in arid regions, followed by an explanation on the runoff concept. Chapter 2 shall also introduce SWAT and MNN and other attributes of previous publications.

Chapter 3 shall introduce the Roodan watershed together with the analysis of usual data and the development of SWAT and MNN. Next, Chapter 4 shall explain the results obtained from the SWAT and MNN models before comparisons are made for the daily flow predicted by both models. These results were obtained from the sensitivity analysis, calibration and validation procedures, and the uncertainty analysis. Lastly, Chapter 5 shall conclude the present study and further suggests appropriate recommendations for future studies.
REFERENCES


