CHAPTER 5

Applications of Fuzzy and Artificial Neural Network to Earthquake Loss Estimations

For risk assessment and retrofit prioritization of structures in the seismic regions of Chiang Rai Municipality, there is an urgent need for a methodology that is rapid, realistic, quantitative, and cost effective. Thus, the methodologies to tradeoff between accuracy and rapidness may prove to be the optimum solution that results in a rapid and reliable seismic risk assessment that is also cost effective. This chapter was to prioritize building retrofit based on earthquake risk assessment. The retrofit prioritization incorporates qualitative and quantitative data which include site seismic hazard, building vulnerability, and importance/exposure factors. Finally, was using an artificial neural network approach for identification of building risk score which more priority by a learning algorithm from fuzzy data. The results confirm that this method is not only a cheaper one but also time saving. Moreover the method is suitable (reliable) when data are uncertain and incomplete.

This chapter provides an overview of the earthquake loss estimations and risk mitigation. Three topics will be discussed in this chapter: (1) Fuzzy application in risk model, (2) Structural repair prioritization of buildings damaged after earthquake using fuzzy logic model and (3) Artificial Neural Network applications in risk model

5.1 Fuzzy Applications in Risk Model

Fuzzy logic is a useful tool for expressing the professional judgments. These judgments may be a verbal statement with vagueness or fuzziness. The example of vagueness in the earthquake risk assessment can be “The building is moderately vulnerable” or “The building is very important” or “The peak ground acceleration is high”. The fuzzy sets describing damaged state of the building are then converted to damage score/total risk score (a real number) by defuzzification process. Earlier study of fuzzy logic application was performed by Zadeh (1965). The study introduced the application of fuzzy logic and fuzzy set theory to risk management. Risk analysis problems contained a mixture of quantitative and qualitative data. Therefore quantitative risk assessment techniques are inadequate for prioritizing risk. Fuzzy logic provides a language with semantics to translate qualitative knowledge into numerical reasoning, which enables modeling complex systems like buildings risk assessment. The strong benefit of fuzzy logic is that it can integrate descriptive or linguistic knowledge and numerical data to fuzzy model and use approximate reasoning algorithms to propagate the uncertainties throughout the decision process. In this study, the risk factors in terms of site seismic hazard, building vulnerability and building important contain relative graded membership, as determined by the combination of scientific process and the processes of human perception and cognition. Fuzzy logic model was hence adopted here taking possibility of incidence and the severity of the risk to be accounted

5.1.1 Building Vulnerability and Final RVS Score

Seismic building vulnerability assessment can be performed by using various approaches depending on the purposes of the evaluation. As it is impossible to perform more advance and detail evaluation individually for all building stocks, this study adopted the assessment method based on sidewalk screening adopted from FEMA154 (2002a). The building vulnerability was identified from rapid visual screening survey. The method is classified as Tier1 seismic performance evaluation of existing buildings. The rapid visual screening firstly considers basic score considering structural type. Then, the score is modified for the final score (S) based on other seismic characteristics of the building, for example building height, building age, soil condition, plan irregularity. The final score (S) obtained implicitly represents seismic performance or damage grade. Nanda and Majhi (2014) suggested that the structure damage could be categorized in different grades depending on their impacts on the seismic strength of the building. Table 5.1 defines the damage grades. A building with higher final score performs better seismic performance. Their damage potential is then classified in lower damage grade. From Table 5.2, the damage of reinforced concrete buildings are classified from Grade 1 to Grade 5 based on the Final Scores.

Table 5.1 Structural scores with damage potential (Nanda and Majhi, 2014)

RVS Final Score (S)	Damage Potential
S<0.3	High probability of Grade 5 damage; Very high probability of Grade 4 Damage
0.3<S<0.7	High probability of Grade 4 damage; Very high probability of Grade 3 Damage
0.7<S<2.0	High probability of Grade 3 damage; Very high probability of Grade 2 Damage
2.0<S<2.5	High probability of Grade 2 damage; Very high probability of Grade 1 Damage
S>2.5	Probability of Grade 1 damage

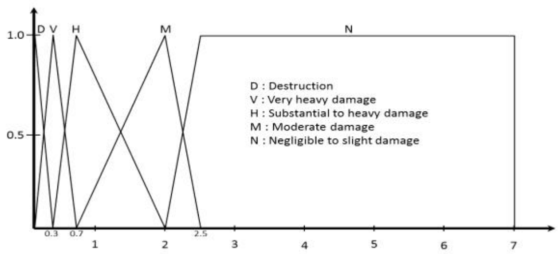
Table 5.2 Classification of damage to reinforced concrete buildings (Nanda and Majhi, 2014)

Damage Stage	Description
Grade 1: Negligible to slight damage (No structural damage, slight non-structural damage)	Fine cracks in plaster over frame members or in walls at the base Fine cracks in partitions and infills.
Grade 2: Moderate damage (Slight structural damage, moderate non-structural damage)	Cracks in columns and beams of frames and in structural walls. Crack in partition and infill walls; fall of brittle cladding and plaster. Falling mortar from the joints of the wall panels
Grade 3: Substantial to heavy damage (Moderate structural damage, heavy non-structural damage)	Cracks in columns and beam-column joints of frames at the base and at joints of coupled walls. Spalling of concrete cover, bucking of reinforced bars. Large cracks in partition and infill walls, failure of individual infill panels.
Grade 4: Very heavy damage (Heavy structural damage, very heavy non-structural damage)	Large cracks in structural elements with compression failure of concrete and fracture of rebars; bond failure of beam reinforcing bars; tilting of columns. Collapse of a few columns or of a single upper floor.
Grade 5: Destruction (very heavy structure damage)	Collapse of ground floor parts (e.g. wings) of the building.

The surveyed final score of buildings in the study area was varied from minimum at 0 and possible maximum at 7. According to the relationship between the final score and damage potential in Table 5.1, the final score was fuzzified into five fuzzy sets of building vulnerability as “Destruction, D”, “very heavy damage, V”, “substantial to heavy damage, H”, “moderate damage, M” and “Negligible to slight damage, N”, respectively. Triangular and trapezoidal fuzzy models were used to relate the linguistic vulnerability levels and the final scores, as shown in Table 5.3. From Table 5.3, the triangular membership function (trimf) contains fuzzy numbers displayed as (a, b, c) where “a” represents the minimum value, “b” represents the most likely values and “c” represents the maximum value. The trapezoidal fuzzy number can be displayed as (a b c d) where “a” represents the minimum value, “b” and “c” equally represent the most likely values and “d” represents the maximum value. The memberships of all the fuzzy sets are drawn in the table. From the figure, the damage potential can be partially classified for the final scores other than the most likely values. For example, for the final score of 0.5, the damage potential can be classified as the combination of the membership degree of “Very heavy damage, V” and “Substantial to heavy damage, H”.

Table 5.3 Proposed vulnerability fuzzy number

Linguistic Parameter	Transformation
Destruction, D	trimf(0,0,0.3)
Very heavy damage, V	trimf(0,0.3,0.7)
Substantial to heavy damage, H	trimf(0.3,0.7,2)
Moderate damage, M	trimf(0.7,2,2.5)
Negligible to slight damage, N	trapmf(2,2.5,7,7)



5.1.2 Peak Ground Acceleration

The peak ground acceleration directly vibrates buildings and generates lateral deformation of the buildings. The earthquake response of the structure is defined by its capacity curve adopted from FEMA (2003). The curve relates lateral load capacity of building with the corresponding lateral deformation, normally at the roof floor. Under the same ground acceleration level, each building responses differently depending on structural types. There are eleven different structural types in Chiang Rai Municipality. Using the capacity curve and the ground acceleration level, the building deformation was estimated. The estimated deformation (d_e) implies level of damages. The larger the lateral deformation, the more severe of damage is induced. Next, the fragility curves were used with the estimated deformation to describe the probability of damage of the analyzed buildings. Therefore, the probability of damage states were applied in PGA(g) fuzzy model, as shown in Figure 5.1.

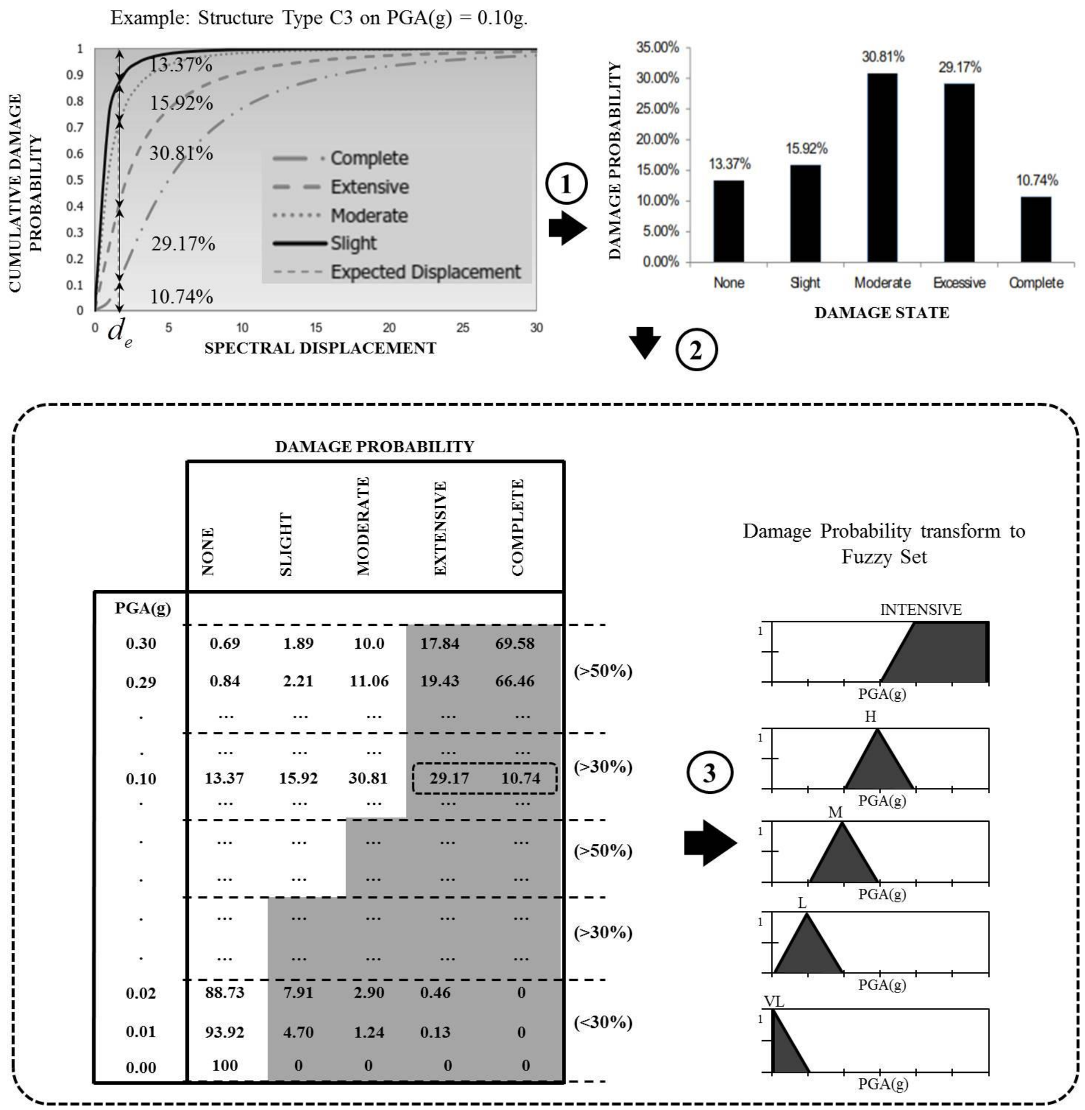


Figure 5.1 The PGA(g) Fuzzy Model

Figure 5.1 shows the PGA(g) fuzzy model. Step1, cumulative probabilities in the fragility curve from each PGA(g) 0.0 to 0.30 transform to the damage state. Step2, separates the level of the Peak Ground Acceleration with damage probability according to the PGA(g) fuzzy model relying on the expert judgments basis was used classification as follows;

- Very Low (VL) is considered as accumulated damage state in slight – complete less than 30%

- Low (L) is considered as accumulated damage state in slight – complete more than 30%

- Moderate (M) is considered as accumulated damage state in moderate – complete more than 50%

- High (H) is considered as accumulated damage state in extensive – complete more than 30%

- Intensive (I) is considered as accumulated damage state in extensive – complete more than 50%

Final Step, transforming the PGA(g) damage range on each linguistic variables to the fuzzy sets.

In the following section, the PGA(g) fuzzy model separates the level of the Peak Ground Acceleration according to the damage level of each structure from cumulative probabilities in the fragility curve. For example, for the concrete frame buildings with unreinforced masonry infill walls (C3);

- Peak Ground Acceleration value of 0.0 – 0.05g is considered as 'Very Low (VL)' ground shaking linguistic which causes accumulated damage to the structure in none - complete level less than 30%.

- Peak Ground Acceleration value 0.05 – 0.07g is considered as 'Low (L)' ground shaking linguistic which causes accumulated damage to the structure in slight - complete level more than 30%.

- Peak Ground Acceleration value 0.07 – 0.10g is considered as 'Moderate (M)' ground shaking linguistic which causes accumulated damage to the structure in moderate-complete level more than 50%.

- Peak Ground Acceleration value 0.10 – 0.16g is considered as ‘High (H)’ ground shaking linguistic which causes accumulated damage to the structure in extensive-complete level more than 30%.

- Peak Ground Acceleration value more than 0.16g is considered as ‘Intensive (I)’ ground shaking linguistic which causes accumulated damage to the structure in extensive-complete level more than 50% respectively.

Table 5.4 shows damage classification for each basic structural type in the study area. The classification was divided into five damage levels, namely very low (VL), low (L), moderate (M), high (H), and intensive (I), and subdivided according to materials and structural systems. In general, each material and structural system is differently capable to remain their stability during earthquake ground motion. In the same levels of deformation, each structural type and material is difference in terms of loading capacity or PGA. Therefore, the fuzzy seismic hazard model was created for all buildings as shown in Tables 5.5 – 5.16.

Table 5.4 Damage classifies from the fragility curve and cumulative damage probabilities for each structure

Structure Type	PGA(g)				
	VL	L	M	H	I
C1	<0.05	0.05-0.07	0.07-0.10	0.10-0.15	>0.15
C2	<0.06	0.06-0.08	0.08-0.12	0.12-0.17	>0.17
C3	<0.05	0.05-0.07	0.07-0.10	0.10-0.16	>0.16
W1	<0.08	0.08-0.19	0.19-0.24	0.24-0.26	>0.26
W2	<0.07	0.07-0.09	0.09-0.14	0.14-0.23	>0.23
S1	<0.05	0.05-0.09	0.09-0.13	0.13-0.16	>0.16
S2	<0.06	0.06-0.10	0.10-0.14	0.14-0.17	>0.17
S3	<0.05	0.05-0.06	0.06-0.08	0.08-0.12	>0.12
URM	<0.07	0.07-0.13	0.13-0.15	0.13-0.17	>0.17
W2C3	<0.07	0.07-0.10	0.10-0.16	0.16-0.23	>0.23
W1C3	<0.07	0.07-0.14	0.14-0.16	0.16-0.25	>0.25

Table 5.5 Transformation of linguistic inputs for seismic hazard, PGA(g) of the structural type C1

Linguistic Parameter	Transformation
Very light, VL	trimf (0,0,0.05)
Light, L	trimf (0,0.05,0.07)
Moderate, M	trimf (0.05,0.07,0.10)
Heavy, H	trimf (0.07,0.10,0.15)
Intensive, I	trapmf (0.10,0.15,0.30,0.30)

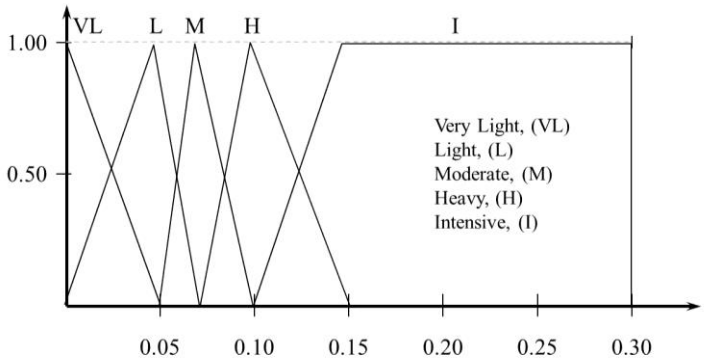


Table 5.6 Transformation of linguistic inputs for seismic hazard, PGA(g) of the structural type C2

Linguistic Parameter	Transformation
Very light, VL	trimf (0,0,0.06)
Light, L	trimf (0,0.06,0.08)
Moderate, M	trimf (0.06,0.08,0.12)
Heavy, H	trimf (0.08,0.12,0.17)
Intensive, I	trapmf (0.12,0.17,0.30,0.30)

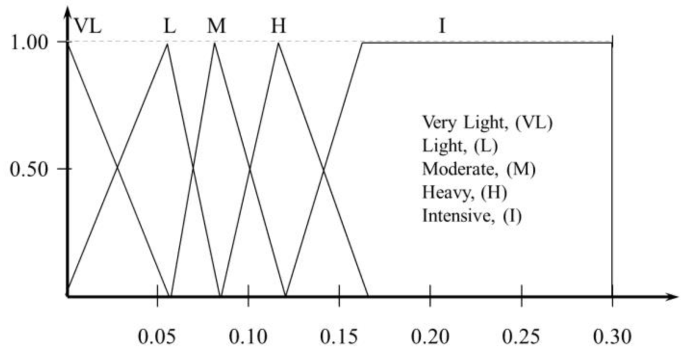


Table 5.7 Transformation of linguistic inputs for seismic hazard, PGA(g) of the structural type C3

Linguistic Parameter	Transformation
Very light, VL	trimf (0,0,0.05)
Light, L	trimf (0,0.05,0.07)
Moderate, M	trimf (0.05,0.07,0.10)
Heavy, H	trimf (0.07,0.10,0.16)
Intensive, I	trapmf (0.10,0.16,0.30,0.30)

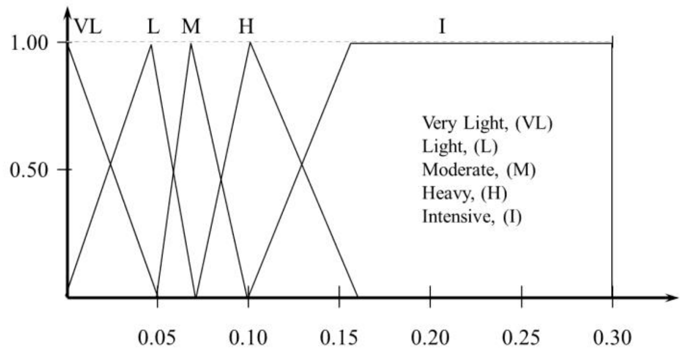


Table 5.8 Transformation of linguistic inputs for seismic hazard, PGA(g) of the structural type W1

Linguistic Parameter	Transformation
Very light, VL	trimf (0,0,0.08)
Light, L	trimf (0,0.08,0.19)
Moderate, M	trimf (0.08,0.19,0.24)
Heavy, H	trimf (0.19,0.24,0.26)
Intensive, I	trapmf (0.24,0.26,0.30,0.30)

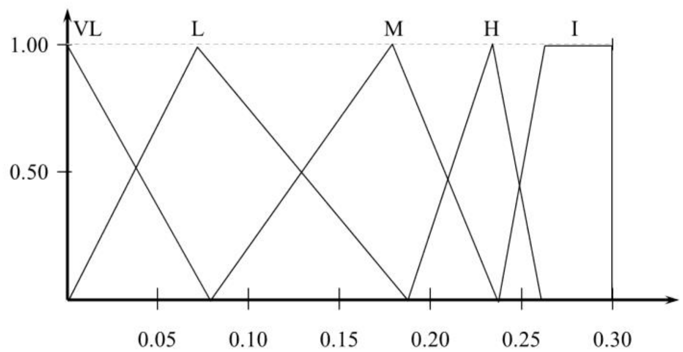


Table 5.9 Transformation of linguistic inputs for seismic hazard, PGA(g) of the structural type W2

Linguistic Parameter	Transformation
Very light, VL	trimf (0,0,0.07)
Light, L	trimf (0,0.07,0.09)
Moderate, M	trimf (0.07,0.09,0.14)
Heavy, H	trimf (0.09,0.14,0.23)
Intensive, I	trapmf (0.14,0.23,0.30,0.30)

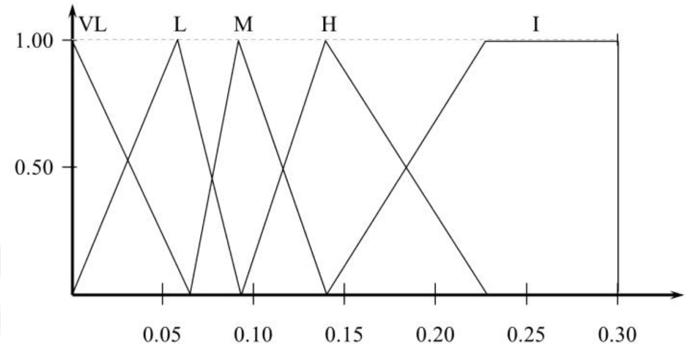


Table 5.10 Transformation of linguistic inputs for seismic hazard, PGA(g) of the structural type S1L

Linguistic Parameter	Transformation
Very light, VL	trimf (0,0,0.05)
Light, L	trimf (0,0.05,0.09)
Moderate, M	trimf (0.05,0.09,0.13)
Heavy, H	trimf (0.09,0.13,0.16)
Intensive, I	trapmf (0.13,0.16,0.30,0.30)

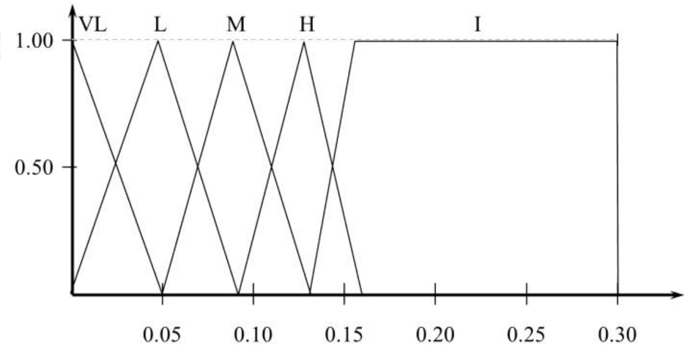


Table 5.11 Transformation of linguistic inputs for seismic hazard, PGA(g) of the structural type S2L

Linguistic Parameter	Transformation
Very light, VL	trimf (0,0,0.06)
Light, L	trimf (0,0.06,0.10)
Moderate, M	trimf (0.06,0.10,0.14)
Heavy, H	trimf (0.10,0.14,0.17)
Intensive, I	trapmf (0.14,0.17,0.30,0.30)

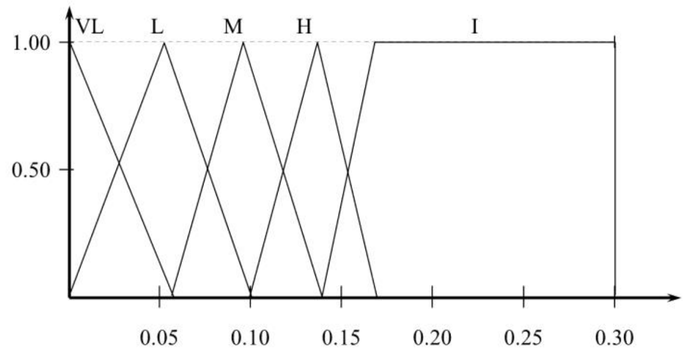


Table 5.12 Transformation of linguistic inputs for seismic hazard, PGA(g) of the structural type S3

Linguistic Parameter	Transformation
Very light, VL	trimf (0,0,0.05)
Light, L	trimf (0,0.05,0.06)
Moderate, M	trimf (0.05,0.06,0.08)
Heavy, H	trimf (0.06,0.08,0.12)
Intensive, I	trapmf (0.08,0.12,0.30,0.30)

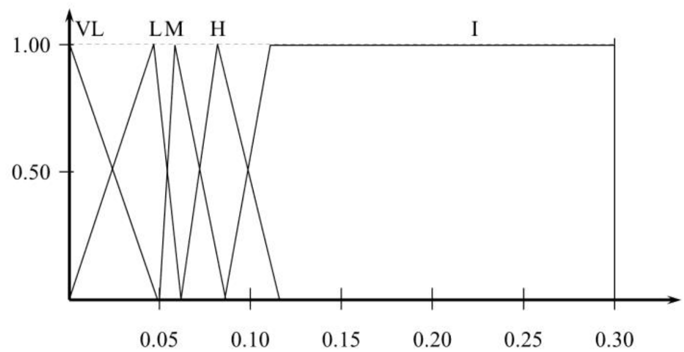


Table 5.13 Transformation of linguistic inputs for seismic hazard, PGA(g) of the structural type URM

Linguistic Parameter	Transformation
Very light, VL	trimf (0,0,0.07)
Light, L	trimf (0,0.07,0.13)
Moderate, M	trimf (0.07,0.13,0.15)
Heavy, H	trimf (0.13,0.15,0.17)
Intensive, I	trapmf (0.15,0.17,0.30,0.30)

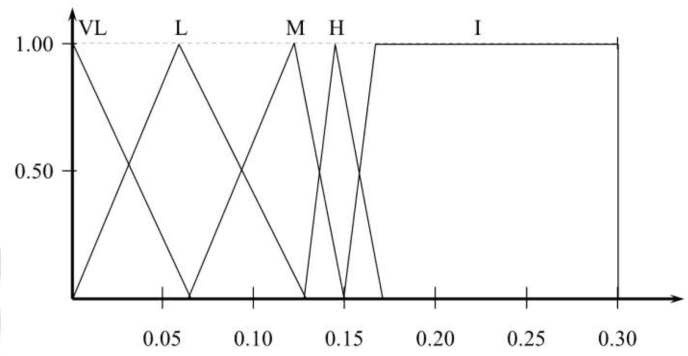


Table 5.14 Transformation of linguistic inputs for seismic hazard, PGA(g) of the structural type W2C3

Linguistic Parameter	Transformation
Very light, VL	trimf (0,0,0.07)
Light, L	trimf (0,0.07,0.10)
Moderate, M	trimf (0.07,0.10,0.16)
Heavy, H	trimf (0.10,0.16,0.23)
Intensive, I	trapmf (0.16,0.23,0.30,0.30)

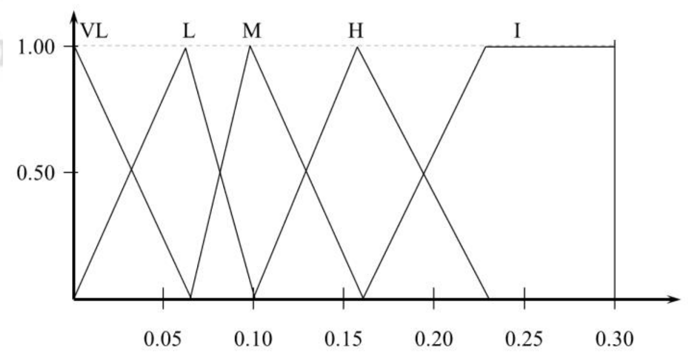
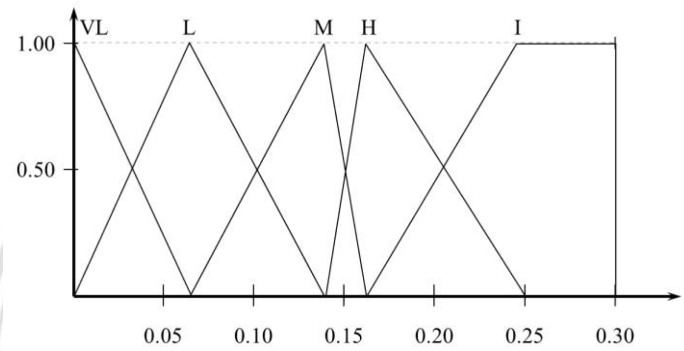


Table 5.15 Transformation of linguistic inputs for seismic hazard, PGA(g) of the structural type W1C3

Linguistic Parameter	Transformation
Very light, VL	trimf (0,0,0.07)
Light, L	trimf (0,0.07,0.14)
Moderate, M	trimf (0.07,0.14,0.16)
Heavy, H	trimf (0.14,0.16,0.25)
Intensive, I	trapmf (0.16,0.25,0.30,0.30)



5.1.3 Fuzzy application in building occupancy

Building occupancy implicitly represents important level of the building. However, the important level is a site dependent and qualitative aspects of human knowledge. There are eleven types of building occupancies in Chiang Rai Municipality. Hence, it needs reasoning process to quantify the important level. It was previously evaluated and weighted by using Analytical Hierarchy Process (AHP) which is a measurement procedure through pairwise comparisons relying on the judgments basis (Saicheur *et al.*, 2013; Saicheur and Hansapinyo, 2016). Questionnaires were distributed to experts for ranking different building occupancies. Figure 5.2 shows the criteria for pairwise comparisons of building exposures computed by integrating building occupancy, likelihood of human casualty, economic importance and the value of property. Table 5.17 shows the ranked buildings occupancy based on the AHP result. The most important building is hospital buildings and the commercial buildings are classified as the least important. The ranked order was applied for fuzzy membership as shown in Figure 5.3. According to the AHP priority result shown in Table 5.16, the triangular type membership function was used to transform the relative important of the nine occupancies into fuzzy variables, as shown in Table 5.16 and Figure 5.3.

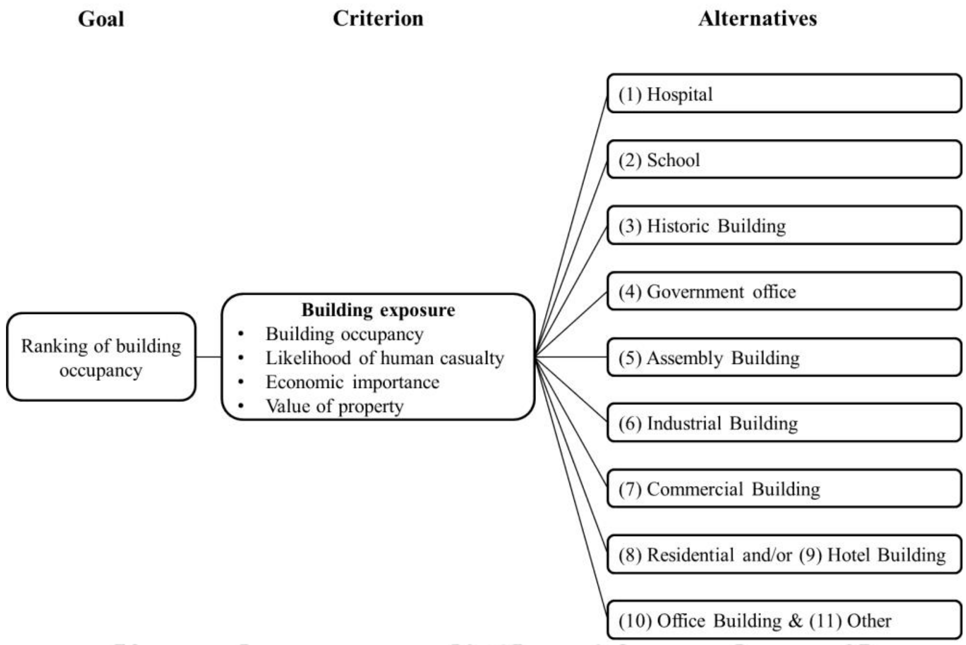


Figure 5.2 AHP hierarchy diagram for ranking of building occupancy

Table 5.16 Ranking of the building occupancy

No.	Building Occupancy	Weight[1],%	Crisp Ranking	Fuzzy Ranking	Membership value
1	Hospital Building	30.43	1	(1,1,2)	(0.875,1,1)
2	School Building	21.11	2	(1,2,3)	(0.75,0.875,1)
3	Historic Building	11.63	3	(2,3,4)	(0.625,0.75,0.875)
4	Government office	9.14	4	(3,4,5)	(0.5,0.625,0.75)
5	Assembly Building	8.46	5	(4,5,6)	(0.375,0.5,0.625)
6	Industrial Building	5.66	6	(5,6,7)	(0.25,0.375,0.5)
7	Residential & Hotel Building	5.29	7	(6,7,8)	(0.125,0.25,0.375)
8	Office Building	4.72	8	(7,8,9)	(0,0.125,0.25)
9	Commercial & Other Building	5.57	9	(8,9,9)	(0,0,0.125)

[1]Saicheur and Hansapinyo, (2016)

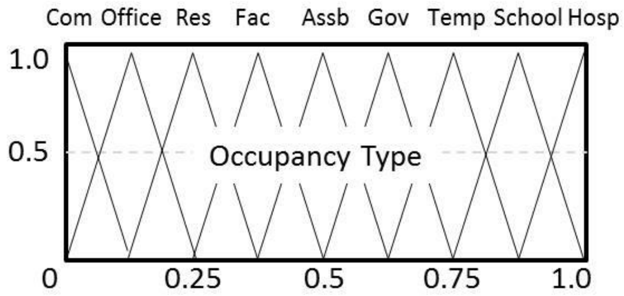


Figure 5.3 Membership function of building occupancy

5.1.4 Fuzzy application in building damageability

Building damageability was determined by integrating the Peak Ground Acceleration value and the building vulnerability score obtained from rapid visual screening method as show in Figure 5.4. The fuzzy rules for decision making relying on the expert judgments basis was used to estimate the building damage, as shown in Table 5.17.

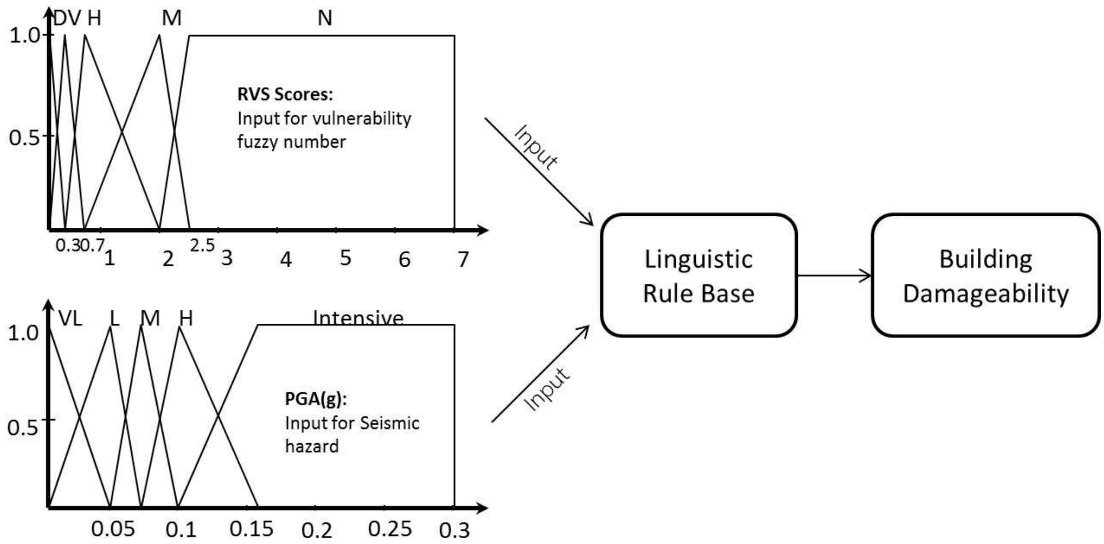


Figure 5.4 Flowchart of the building damageability

Table 5.17 Fuzzy associative memory (FAM) for building damage

Building vulnerability \ PGA(g)	VL	L	M	H	I
Negligible to slight damage, N	N	N	L	M	H
Moderate damage, M	N	L	M	M	H
Substantial to heavy damage, H	L	M	M	H	H
Very heavy damage, V	M	M	H	H	S
Destruction, D	M	H	H	S	S

From Table 5.17, the buildings damage classification are expressed as "N: none damage", "L: light damage", "M: moderate damage", "H: heavy damage" and "S: severe damage" categories. The fuzzy logic model includes combined rules process. This section shown each structure type has total 25 rules are framed for building damage score and presents as follows.

Example: Linguistic $Rule_i$ for Building Type C3

Rule 1: IF Building type C3 damage opportunity level is Negligible AND PGA level is Very Low
THEN Damage score is None;

Rule 2: IF Building type C3 damage opportunity level is Negligible AND PGA level is Low
THEN Damage score is None;

Rule 3: IF Building type C3 damage opportunity level is Negligible AND PGA level is Moderate
THEN Damage score is Light;

Rule 4: IF Building type C3 damage opportunity level is Negligible AND PGA level is Heavy
THEN Damage score is Moderate;

Rule 5: IF Building type C3 damage opportunity level is Negligible AND PGA level is Intensive
THEN Damage score is Heavy;

Rule 6: IF Building type C3 damage opportunity level is Moderate AND PGA level is Very Low

THEN Damage score is None;

Rule 7: IF Building type C3 damage opportunity level is Moderate AND PGA level is Low

THEN Damage score is Light;

Rule 8: IF Building type C3 damage opportunity level is Moderate AND PGA level is Moderate

THEN Damage score is Moderate;

Rule 9: IF Building type C3 damage opportunity level is Moderate AND PGA level is Heavy

THEN Damage score is Moderate;

Rule 10: IF Building type C3 damage opportunity level is Moderate AND PGA level is Intensive

THEN Damage score is Heavy;

Rule 11: IF Building type C3 damage opportunity level is Heavy AND PGA level is Very Low

THEN Damage score is Light;

Rule 12: IF Building type C3 damage opportunity level is Heavy AND PGA level is Low

THEN Damage score is Moderate;

Rule 13: IF Building type C3 damage opportunity level is Heavy AND PGA level is Moderate

THEN Damage score is Moderate;

Rule 14: IF Building type C3 damage opportunity level is Heavy AND PGA level is Heavy

THEN Damage score is Heavy;

Rule 15: IF Building type C3 damage opportunity level is Heavy AND PGA level is Intensive

THEN Damage score is Heavy;

Rule 16: IF Building type C3 damage opportunity level is Very Heavy AND PGA level is Very Low

THEN Damage score is Moderate;

Rule 17: IF Building type C3 damage opportunity level is Very Heavy AND PGA level is Low

THEN Damage score is Moderate;

Rule 18: IF Building type C3 damage opportunity level is Very Heavy AND PGA level is Moderate

THEN Damage score is Heavy;

Rule 19: IF Building type C3 damage opportunity level is Very Heavy AND PGA level is Heavy

THEN Damage score is Heavy;

Rule 20: IF Building type C3 damage opportunity level is Very Heavy AND PGA level is Intensive

THEN Damage score is Severe;

Rule 21: IF Building type C3 damage opportunity level is Destruction AND PGA level is Very Low

THEN Damage score is Moderate;

Rule 22: IF Building type C3 damage opportunity level is Destruction AND PGA level is Low

THEN Damage score is Heavy;

Rule 23: IF Building type C3 damage opportunity level is Destruction AND PGA level is Moderate

THEN Damage score is Heavy;

Rule 24: IF Building type C3 damage opportunity level is Destruction AND PGA level is Heavy

THEN Damage score is Severe;

Rule 25: IF Building type C3 damage opportunity level is Destruction AND PGA level is Intensive

THEN Damage score is Severe;

An example of defuzzification in building Type C3 is shown here. With the peak ground acceleration value of 0.15g and the RVS-score of 0.5, the vulnerability level of the building is very heavy damage.

Therefore, gives a single crisp value from weighted average method as an output after defuzzifying the aggregate fuzzy set, that leads to damage type is collapse with damage score 0.817.

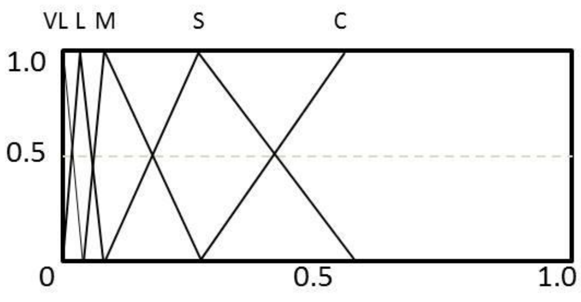
5.1.5 Fuzzy application for the Total Risk Scores

Finally, the total risk score was computed by integrating the building important (Section 5.1.3) and the building damaged scores (Section 5.1.4). The result of damage score in section 5.1.4 is transfer to fuzzy input of Total Risk score as show in Fig. 5.5. The result of damage score is based on the damage type descriptions provided FEMA (2000). In addition, the numerical values that represent the damage factor of ATC (1985) were related to the damage type descriptions as shown in Table 5.18.

Table 5.19 presents the resulting correlation between building occupancy and damage score. The triangular membership function have fuzzy numbers can be displayed as (a b c) where “a” represents the minimum score, “b” represent the most likely score, and “c” represents the maximum score.

Table 5.18 Correlation between damage type and damage score

Damage Type	Damage Score	Transformation
Very Light, VL	0.0 - 0.1	trimf(0,0,0.01)
Light, L	0.1 - 10	trimf(0,0.01,0.1)
Moderate, M	10 - 30	trimf(0.01,0.1,0.3)
Severe, S	30 - 60	trimf(0.1,0.3,0.6)
Collapse, C	60 - 100	trapmf(0.3,0.6,1,1)



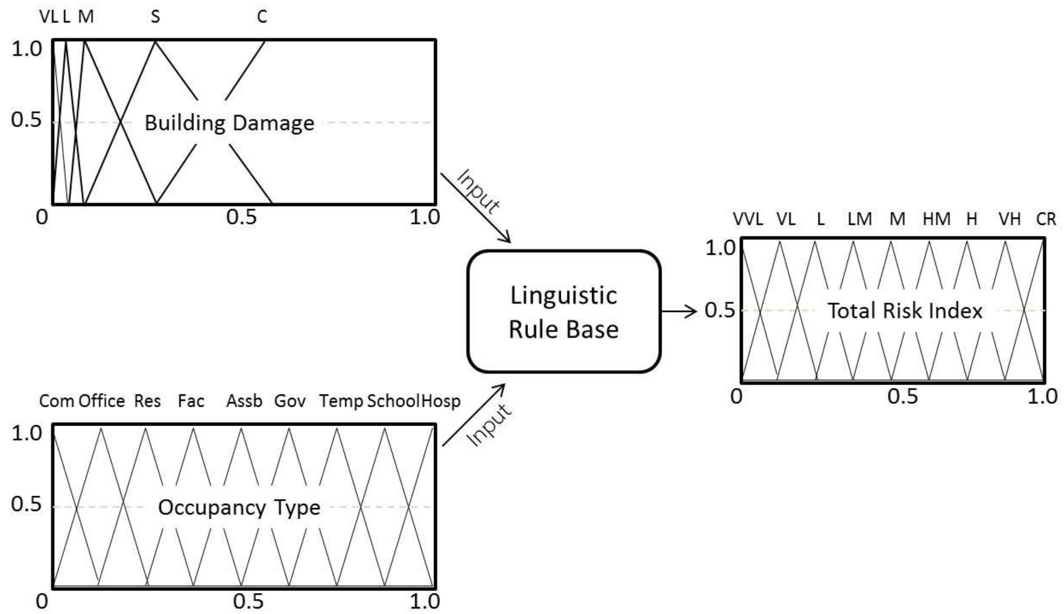


Figure 5.5 Flowchart of the Total Risk Index

Table 5.19 Fuzzy associative memory (FAM) for total risk score

Type \ Damage	VL	L	M	S	C
Commercial	VVL	VVL	VL	L	LM
Office	VVL	VL	L	LM	M
House, Residential	VL	L	LM	M	M
Factory	L	LM	M	M	HM
Assembly	LM	M	M	HM	HM
Gov. office	M	M	HM	HM	H
Temple	M	HM	HM	H	VH
School	HM	HM	H	VH	CR
Hospital	HM	H	VH	CR	CR

Especially for the total risk score was computed by integrating the building importance and the building damaged that has total 45 rules are presents in Table 5.19. The Total Risk Score are expressed in term of fuzzy words in proper sentences (statement) such as “Very Very Low, VVL ”, “Very light, VL”, “Light, L”, “Light-moderate, LM”, “Moderate, M”, “High-moderate, HM”, “High, H”, “Very-high” and “Critical, CR” , respectively..

Example: Linguistic Rule$_i$ for Building Type i

Rule 1: IF Building Occupancy type is Commercial AND
Building Damage is Very Low
THEN Total Risk Score is Very-Very Low;

Rule 2: IF Building Occupancy type is Commercial AND
Building Damage is Low
THEN Total Risk Score is Very-Very Low;

Rule 3: IF Building Occupancy type is Commercial AND
Building Damage is Moderate
THEN Total Risk Score is Very Low;

Rule 4: IF Building Occupancy type is Commercial AND
Building Damage is Severe
THEN Total Risk Score is Low;

Rule 5: IF Building Occupancy type is Commercial AND
Building Damage is Collapse
THEN Total Risk Score is Low-Moderate;

Rule 6: IF Building Occupancy type is Office AND
Building Damage is Very Low
THEN Total Risk Score is Very-Very Low;

Rule 7: IF Building Occupancy type is Office AND
Building Damage is Low
THEN Total Risk Score is Very Low;

Rule 8: IF Building Occupancy type is Office AND
Building Damage is Moderate
THEN Total Risk Score is Low;

Rule 9: IF Building Occupancy type is Office AND
Building Damage is Severe
THEN Total Risk Score is Low-Moderate;

Rule 10: IF Building Occupancy type is Office AND
Building Damage is Collapse
THEN Total Risk Score is Moderate;

Rule 11: IF Building Occupancy type is Residential AND

Building Damage is Very Low

THEN Total Risk Score is Very Low;

Rule 12: IF Building Occupancy type is Residential AND

Building Damage is Low

THEN Total Risk Score is Low;

Rule 13: IF Building Occupancy type is Residential AND

Building Damage is Moderate

THEN Total Risk Score is Low-Moderate;

Rule 14: IF Building Occupancy type is Residential AND

Building Damage is Severe

THEN Total Risk Score is Moderate;

Rule 15: IF Building Occupancy type is Residential AND

Building Damage is Collapse

THEN Total Risk Score is Moderate;

Rule 16: IF Building Occupancy type is Factory AND

Building Damage is Very Low

THEN Total Risk Score is Low;

Rule 17: IF Building Occupancy type is Factory AND

Building Damage is Low

THEN Total Risk Score is Low-Moderate;

Rule 18: IF Building Occupancy type is Factory AND

Building Damage is Moderate

THEN Total Risk Score is Moderate;

Rule 19: IF Building Occupancy type is Factory AND

Building Damage is Severe

THEN Total Risk Score is Moderate;

Rule 20: IF Building Occupancy type is Factory AND

Building Damage is Collapse

THEN Total Risk Score is High-Moderate;

Rule 21: IF Building Occupancy type is Assembly AND

Building Damage is Very Low

THEN Total Risk Score is Low-Moderate;

Rule 22: IF Building Occupancy type is Assembly AND
Building Damage is Low
THEN Total Risk Score is Moderate;

Rule 23: IF Building Occupancy type is Assembly AND
Building Damage is Moderate
THEN Total Risk Score is Moderate;

Rule 24: IF Building Occupancy type is Assembly AND
Building Damage is Severe
THEN Total Risk Score is High-Moderate;

Rule 25: IF Building Occupancy type is Assembly AND
Building Damage is Collapse
THEN Total Risk Score is High-Moderate;

Rule 26: IF Building Occupancy type is Government Office AND
Building Damage is Very Low
THEN Total Risk Score is Moderate;

Rule 27: IF Building Occupancy type is Government Office AND
Building Damage is Low
THEN Total Risk Score is Moderate;

Rule 28: IF Building Occupancy type is Government Office AND
Building Damage is Moderate
THEN Total Risk Score is High-Moderate;

Rule 29: IF Building Occupancy type is Government Office AND
Building Damage is Severe
THEN Total Risk Score is High-Moderate;

Rule 30: IF Building Occupancy type is Government Office AND
Building Damage is Collapse
THEN Total Risk Score is High;

Rule 31: IF Building Occupancy type is Temple AND
Building Damage is Very Low
THEN Total Risk Score is Moderate;

Rule 32: IF Building Occupancy type is Temple AND
Building Damage is Low

THEN Total Risk Score is High-Moderate;

Rule 33: IF Building Occupancy type is Temple AND
Building Damage is Moderate
THEN Total Risk Score is High-Moderate;

Rule 34: IF Building Occupancy type is Temple AND
Building Damage is Severe
THEN Total Risk Score is High;

Rule 35: IF Building Occupancy type is Temple AND
Building Damage is Collapse
THEN Total Risk Score is Very-High;

Rule 36: IF Building Occupancy type is School AND
Building Damage is Very Low
THEN Total Risk Score is High-Moderate;

Rule 37: IF Building Occupancy type is School AND
Building Damage is Low
THEN Total Risk Score is High-Moderate;

Rule 38: IF Building Occupancy type is School AND
Building Damage is Moderate
THEN Total Risk Score is High;

Rule 39: IF Building Occupancy type is School AND
Building Damage is Severe
THEN Total Risk Score is Very-High;

Rule 40: IF Building Occupancy type is School AND
Building Damage is Collapse
THEN Total Risk Score is Critical;

Rule 41: IF Building Occupancy type is Hospital AND
Building Damage is Very Low
THEN Total Risk Score is High-Moderate;

Rule 42: IF Building Occupancy type is Hospital AND
Building Damage is Low
THEN Total Risk Score is High;

Rule 43: IF Building Occupancy type is Hospital AND

Building Damage is Moderate

THEN Total Risk Score is Very-High;

Rule 44: IF Building Occupancy type is Hospital AND

Building Damage is Severe

THEN Total Risk Score is Critical;

Rule 45: IF Building Occupancy type is Hospital AND

Building Damage is Collapse

THEN Total Risk Score is Critical;

Therefore, an example of defuzzification result in building occupancy type Hospital (9), and Damage score equal 0.4 leads to the Total Risk Score is 0.957, whereas the building which less important e.g. housing (3) has damage score equal 0.9 that leads to the Total Risk Score is 0.500 only. Figures 5.7 show the spatial distribution of building's Total Risk Score.

5.1.6 Result of Fuzzy Model

From the analytical result in the fuzzy model, the Damage Score and Total Risk Score of buildings in the study area are present in Figures 5.6 – 5.7, respectively. Figure 5.6 shows the distribution of the damage score of the buildings in Chiang Rai Municipality when subjected to the earthquake scenario. It illustrates that the maximum damage mostly occurred at the epicenter. In the following section, the total risk score which are integrating from the building importance and the building damaged in previous results. Overall, it illustrates that the buildings which are critical after assumed earthquake event that can presents in Figure 5.7.

However, with a limitation on budget and time, incremental upgrading focusing on important buildings has been generally considered. Table 5.20, shows the example of six buildings were selected and evaluated for the total risk score. That showed which buildings are critical for decision maker select to retrofits. From the application of the proposed fuzzy model, the hospital building is the first priority needed to retrofits with damage score of 0.808 and the total risk score of 0.962. The factory has damage score of 0.986 due to the higher damage score compared to the school building (0.222), temple (0.581) and government building (0.657), respectively. However, the factory, due to lower total risk score (0.625) compared to the school building, temple and government building, have the total risk score of 0.823, 0.864 and 0.750, respectively. The building with less damage score and low important; such as housing has the total risk score of 0.408 which is identified as non-urgent to retrofits.

Table 5.20 Example buildings with Total Risk Score from fuzzy model

Building Name	Type	Occupancy	RVS, Final Score	PGA(g)	Damage Score	Total Risk Score
Hospital, id. 49785	C3	Hospital	3.6	0.169	0.808	0.962
Local School, id. 38959	W1C3	School	4.6	0.143	0.222	0.823
Temple, id. 664	W2C3	Historic	2.7	0.182	0.581	0.864
Government, id.38906	C3	Gov. Office	2.6	0.133	0.657	0.750
Factory, id. 25972	C3	Industrial	2.1	0.178	0.808	0.625
House, id. 11883	W1	Residential	6.6	0.114	0.145	0.408

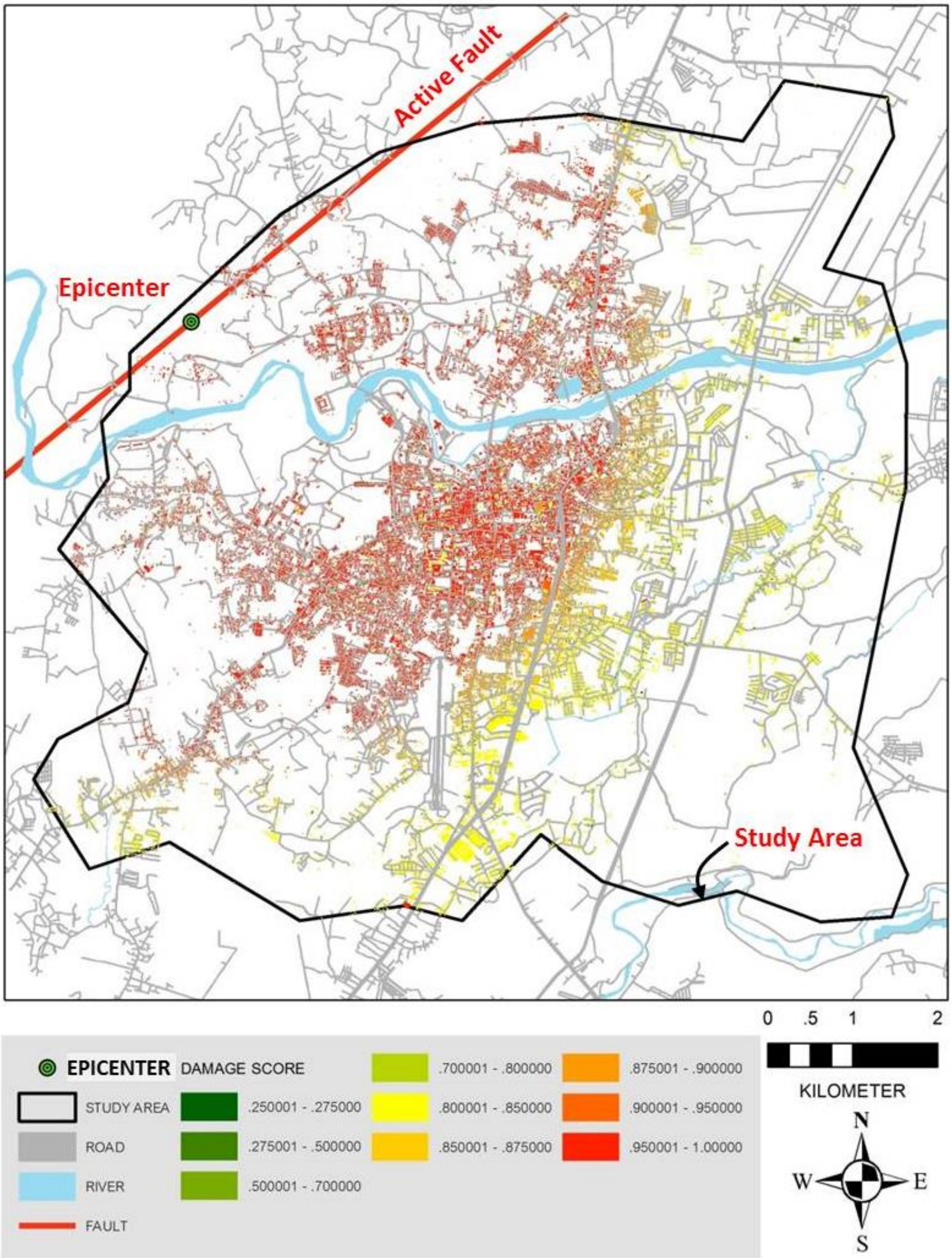


Figure 5.6 Distribution of Damage Score of buildings

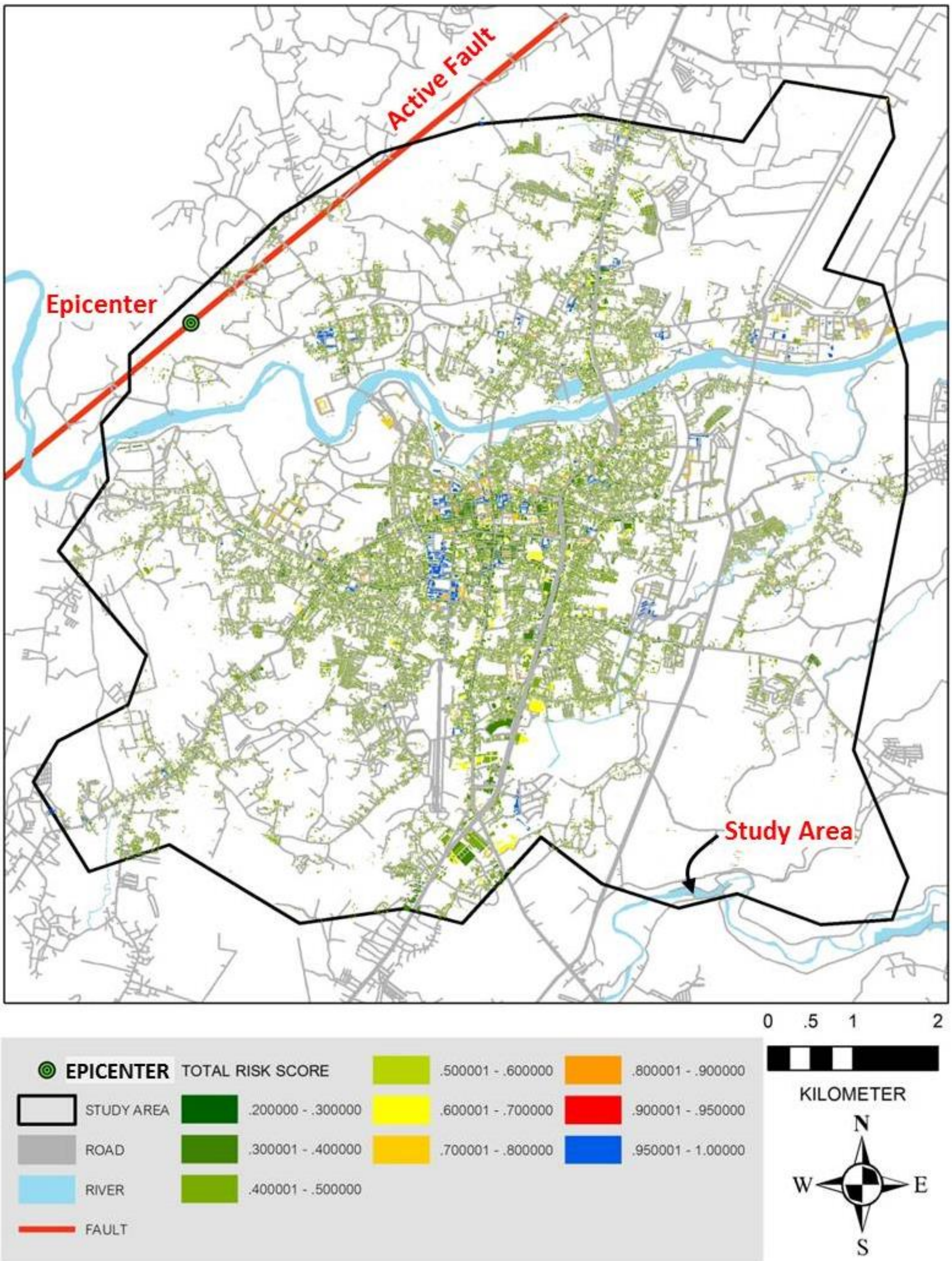


Figure 5.7 Distribution of Total Risk Score of buildings

5.2 Structural Repair Prioritization of Buildings Damaged After Earthquake Using Fuzzy Logic Model

This section show how using fuzzy logic was applied in another application for prioritization of building damaged. After, Mae Lao earthquake with a magnitude of 6.3 occurred on May 5, 2014. It was the strongest earthquake ever recorded in Thailand, according to National Disaster Warning Center. The building damage can be summarized according to the buildings damage investigation leveled by green, yellow and red paint-sign ranged from low to high damage as seen in Table 5.21 and Figure 5.8, respectively.

Table 5.21 Summary of the buildings damaged level (Ornthammarath, 2014)

District	R (Red) Heavy damage	Y (Yellow) Moderate damage	G (Green) Slight damage
Mae Lao	378	1,631	2,892
Mae Suai	34	39	1,224
Mueang Chaing Rai	34	89	639
Phan	152	578	3,022
Total	598	2,337	7,777

Figure 5.8 Building damage levels (Green, Yellow, Red with paint-sign), categorize by Department of Public Works and Town & Country Planning, Thailand

The color labeled during the site investigation after the earthquake was performed suddenly to classified and recommended for the utilization. The utilization, according to the damage level can be classified as red and yellow painted buildings were unable to use and green buildings were useable. It can be seen from Table 5.21 that 2,935 buildings could not be used and needed to be repaired (red and yellow).

Generally, the building repair is a major task as soon as after the hit of a strong earthquake. However, with limitations of engineers, equipment and budget, it is impossible to repair all buildings in the same time. The procedure to identify critical buildings and prioritize their repairing requirements is then an important process. Nevertheless, the damage identification for the utilization was performed with limited time. In addition, with high variation of engineering judgments of the investigators (Tanaka, 2008), the result of the damage investigation was very subjective. Furthermore, there are other factors that need to be used for the prioritization assessment than the building damaged level such as indirect impact and building occupancy. The considered factors can then be said as the vague information and not easy to make decision. With the trend of seismic risk assessment considering the subjective inputs, there have been a number of researchers concerned with fuzzy loss estimation. Deb and Kumar (2004), Sen (2010), Sen (2011), and Haoxiang *et al*. (2013) and Shirashi *et al*. (2005) showed the applicability of fuzzy methodology to seismic damage assessment in reinforced concrete buildings, which converts the fuzzy linguistic variable to index number that corresponding to damage state. Therefore, the fuzzy logic developed for managing the uncertain data was adopted here to approximate the vague information of the repair prioritization factors to the numerical data. Using the IF-THEN rule based forms, an important index considering the vague information of each building leading to decision making were proposed.

5.2.1 Categorization of earthquake damage

After the Mae Lao Earthquake occurred in Chiang Rai Province, buildings in the area were damaged and urgent building investigation was needed. Department of Public Works and Town & Country Planning of Thailand produced a procedure and document to collect buildings data for management and repair (as Table 5.22). Based on the crack damage pattern and severity, the inspection records were categorized as slight, moderate and heavy damages. Visually represented by color label, the three damage levels were referred as green, yellow and red, respectively. However, the damage level defined in the three categories was vague information. The same damage level can be defined in different categories. Likewise, different damage level can be defined in the same category. In other words, the level covers very wide range of damage level. Although the damage severity is unable to be clearly defined, the identified level is distinctive. Hereinafter, the method is called distinctive damage based method or DDB. In addition, the information was not enough to help the government officer/building owners to identify which building was more critical and need a repair priority. Finally, the categorization contains the following drawbacks;

- Only damage level was considered ignoring other factors, including the building occupancy and consequence.
- Color identification is not clear.

Therefore, fuzzy logic is essentially a system for dealing with uncertainly data and approximate information to solving this problem.

Table 5.22 Check lists for categorization of earthquake damage

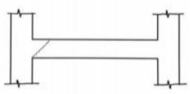
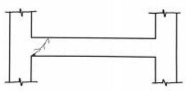
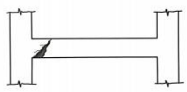
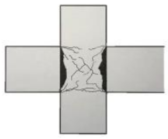
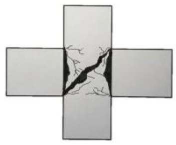
Inspector Information:			
Building Information	Structure Type	Occupancy	Physical Information
Building Irregularity	Yes/No		
Damage Information			
Damage Level	Slight	Moderate	Heavy
Beam			
Column			
Wall			

Table 5.22 Check lists for categorization of earthquake damage (continued)

Damage Information			
Damage Level	Slight	Moderate	Heavy
Joint			
Other Damaged			
Photo			
Summary	G	Y	R

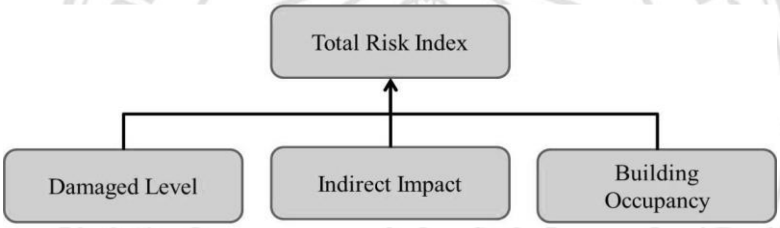


Figure 5.9 Total Risk Index assessment model

5.2.2 Methodology

This section adopted mathematical fuzzy logic model to analyze total risk index identifying building priority to repair. The fuzzy risk index was computed by integrating the painted-sign that reflects the building damaged level, indirect impact and building occupancy, as shown in Figure 5.9. The crisp result was computed by fuzzy inferences system.

1) Fuzzy application in building damaged level

Building damaged models were identified from visual screening survey and then painted-sign was made on each building that reflects building damage level, such as green painted-sign (slight damage), yellow painted-sign (moderate damage) and red paint-sign (heavy damage or collapse). Figure 5.10 shows the membership functions for crisp sets. A building with a damage level of 0.0 belongs to the set of slight damage level (Green painted-sign). Likewise, a building where damage level of 0.5 belongs to the set of moderate damage level (Yellow painted-sign) and 1.0 belongs to the set of heavy damage level (Red painted-sign), respectively.

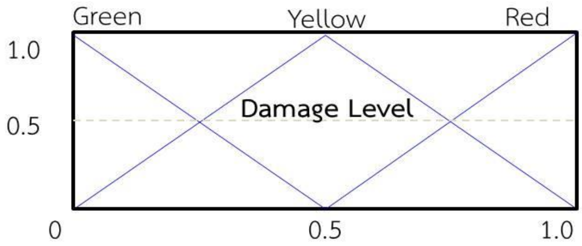


Figure 5.10 Membership function of damage level

However, actually there are many occasions to judge in trouble for painted-sign or represents accuracy damaged level. Therefore, fuzzy logic is essentially a system for approximate building damage level. In fuzzy logic, an objective may have participation in more than one set at same time. Hence, damage level between green and yellow, or light yellow such as 0.2, may participate in both sets for slight damage and moderate damage. As this case damage level of 0.2, the participation in set of slight damage (green) decreases and the participation in the set of moderate damage increases. Thus, the membership of the fuzzy building damage level are trimf(0,0,0.5) for slight damage, trimf(0,0.5,1) for moderate damage and trimf(0.5,1,1) for heavy damage or collapse.

2) Fuzzy application in direct impact

The indirect impact is the consequence loss from the building damage (direct impact). It can be exampled as the damage of school buildings leading to the shutting down of education activities or stopping of medical services from the collapse of hospital buildings. The indirect impact was evaluated by expert engineers or those involved in management level to assess the urgent need for repair. It might have an impact on the community, such as hospitals, which are vital in helping victims and other government buildings. The fuzzy indirect impact based on the triangular distribution is shown in Figure 5.11.

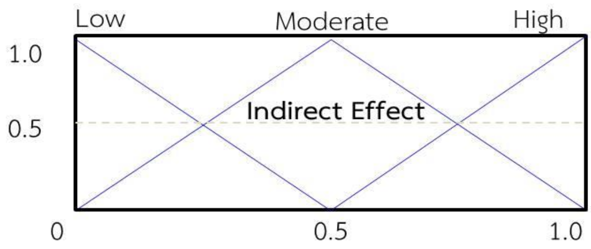


Figure 5.11 Membership function of indirect impact

For example, indirect impact is between moderate and high such as 0.8, may participate in both sets for moderate and high impact. As this case, the participation in set of moderate impact decreases and the participation in the set of high impact increases. The corresponding fuzzy number are trimf(0,0,0.5) for low impact, trimf(0,0.5,1) for moderate impact and trimf(0.5,1,1) for high impact.

3) Fuzzy application in building occupancy or building importance

Risk analysis problems contain a mixture of quantitative and qualitative data; therefore quantitative risk assessment techniques are inadequate for prioritizing risk (Nieto-Morote and Ruz-Vila, 2011). Building occupancy represents important level for each building. However, the important level cannot be clearly defined and it is site dependent. The level of 9 building occupancies was first evaluated qualitatively and weighted by Analytic Hierarchy Process (AHP). The Analytic Hierarchy Process (Saaty,1980; Saaty, 2008) is a measurement procedure through pairwise comparisons relying on the judgments of experts. In order to carry out the weighted building importance, 10 questionnaires were distributed to expert engineers for ranking different building occupancy according to the Analytic Hierarchy Process. The criterion for pairwise comparisons in building exposure and result of ranked buildings occupancy was shown in Chapter 5. The most important building is hospital buildings and the commercial buildings are classified as the less important. The ranked order was then equally applied for fuzzy membership as shown in Figure 5.12, based on the triangular relationship.

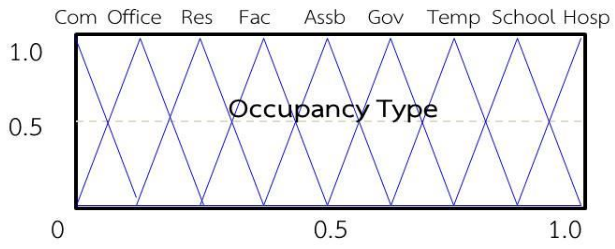


Figure 5.12 Membership function of building occupancy

5.2.3 Fuzzy inference for the Total Risk Index

The total risk index is the output from the fuzzy rules inference that was computed by integrating the building damage level (Figure 5.10), indirect impact (Figure 5.11) and the building importance (Figure 5.12), as shown in Figure 5.13, using IF_THEN rule base. An example can be expressed below. The analysis totally consists of 81 statements (3 (building damage) x 3(indirect impact) x 9(building occupancy)).

Rule1 : IF (Building Damage is Red) AND (Indirect is Low) AND (Occupancy is School)

THEN Risk is Moderate-High

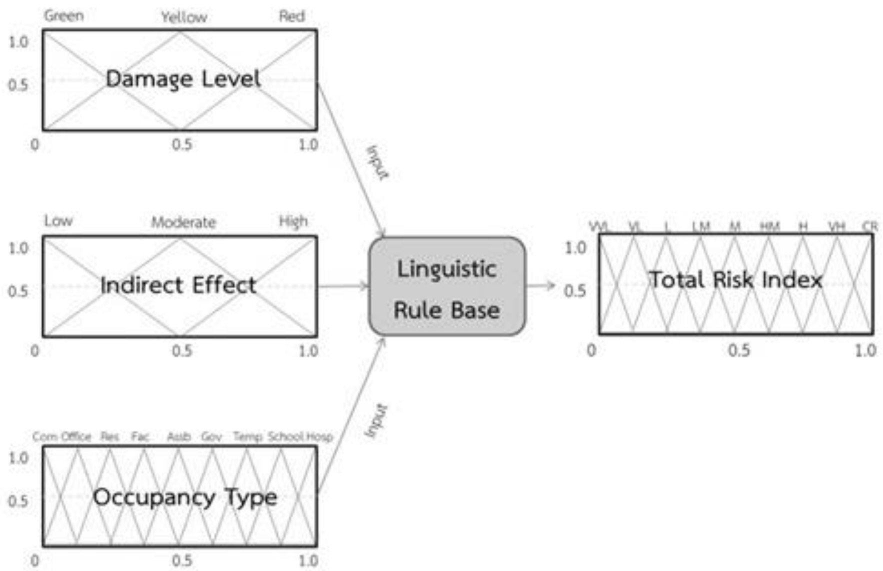


Figure 5.13 Fuzzy inference of Total Risk Index

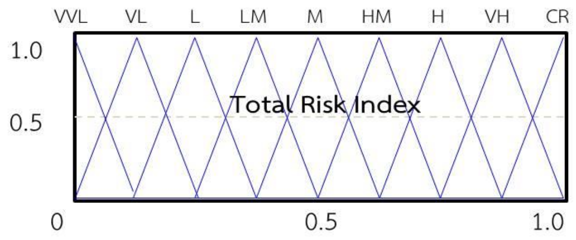
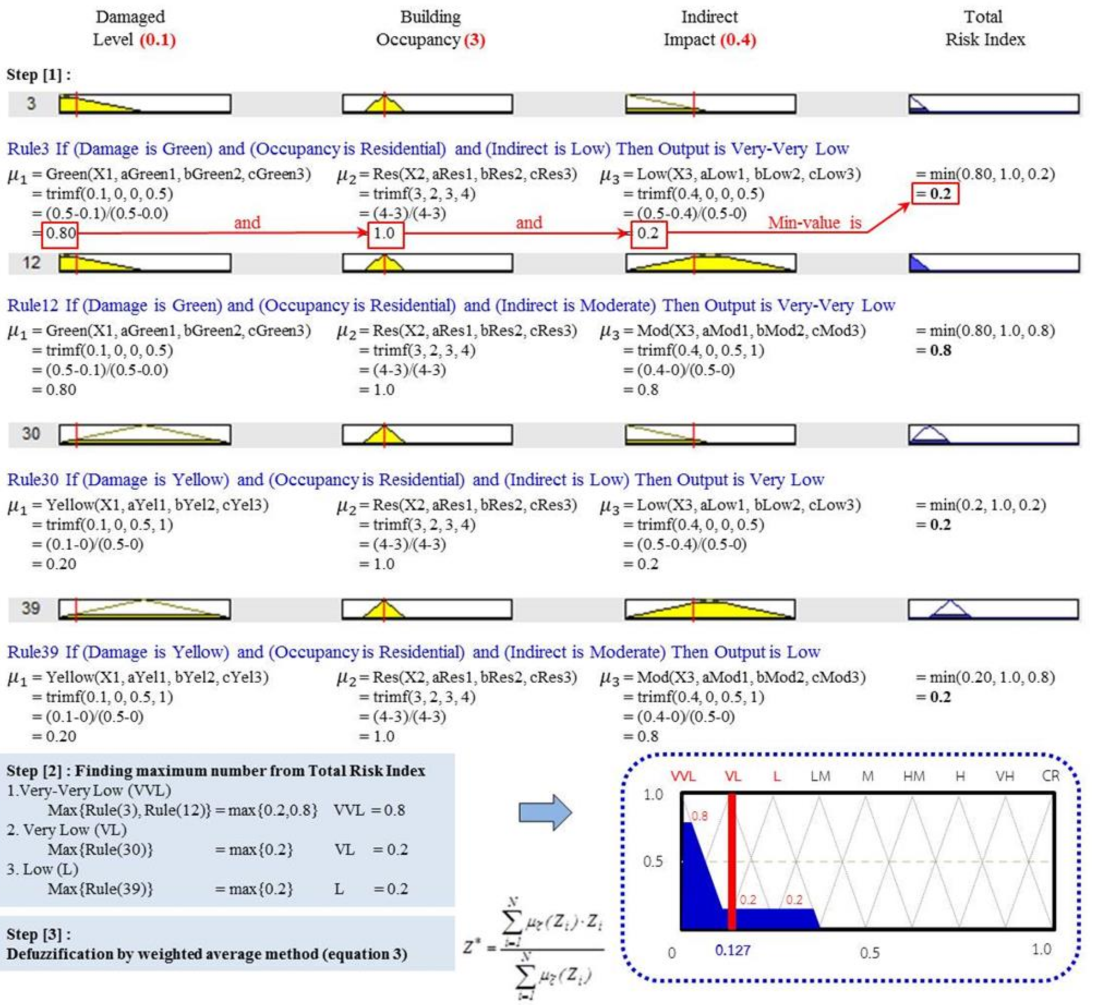


Figure 5.14 Membership function of Total Risk Index

The total risk index is classified into 9 levels expressed as “Very-Very Low, VVL ”, “Very Low, VL”, “Low, L”, “Low-Moderate, LM”, “Moderate, M”, “High-Moderate, HM”, “High, H”, “Very-High, VH” and “Critical, CR” (Figure 5.14). Finally, transform the total risk index to crisp values through defuzzification using weighted average method.

5.2.4 Application of the Fuzzy logic model

The fuzzy model established in Section 5.2.3 considering the vague inputs was used for decision making on prioritization of the damaged buildings to be repaired. To show the applicability of the fuzzy logic model, for an example, Figure 5.15 shows determination of the total risk index using the fuzzy model of a house.



$$Z^* = \frac{\sum_{i=1}^{N} \mu_{\tilde{z}}(Z_i) \cdot Z_i}{\sum_{i=1}^{N} \mu_{\tilde{z}}(Z_i)}$$

$$\frac{(0 \times 0) + (.8 \times .025) + (.5 \times .0625) + (.2 \times .1) + (.2 \times .125) + (.2 \times .1875) + (.2 \times .25) + (.2 \times .3125) + (.2 \times .35) + (0 \times .375)}{0 + 0.8 + 0.5 + 0.2 + 0.2 + 0.2 + 0.2 + 0.2 + 0.2 + 0} = \frac{0.31625}{2.5} = 0.127$$

Figure 5.15 Defuzzification process to crisp values

The damage level was evaluated as 0.1 containing vague decision between damage levels colored as green (80%) and yellow color (20%). The important level of the building was clearly defined as 3.0, without vague information, for the house. The indirect impact level was 0.4 having vague decision between low (20%) and moderate (80%) impact level. With the total 81 rule statements, however, only some statements were related. Then, transformation of the fuzzy inference to the total crisp risk index using weighted average method as seen in Chapter 5 were performed. The execution of the fuzzy inference mechanism consists of three connectives, (1) aggregation of the antecedents in each rule i.e. use AND connectives, (2) implication i.e. use IF-THEN connectives, and (3) aggregation of the rules i.e. ALSO connectives. However, at present (House damaged level 0.1, occupancy type 3 and indirect impact equal 0.4), only 4 statements were related such as;

Rule no 3. If (Damage is Green) and (Occupancy is Residential) and (Indirect is Low) then output is Very-Very Low

Rule no 12. If (Damage is Green) and (Occupancy is Residential) and (Indirect is Moderate) then output is Very-Very Low

Rule no 30. If (Damage is Yellow) and (Occupancy is Residential) and (Indirect is Low) then output is Very Low

Rule no 39. If (Damage is Yellow) and (Occupancy is Residential) and (Indirect is Moderate) then output is Low.

Result of the analysis was found that the total risk index equals to 0.127. For considering damaged buildings in the affected area, the total risk index of the buildings can be ranked and decision making on repair need can be then made.

As seen in Table 5.23, six buildings were evaluated for the total risk showing building priority need to repair. Figure 5.16 shows building damaged assessment comparing the distinctive damage based method (DDB) and the proposed fuzzy method (PFM). The proposed fuzzy method clearly defines the repair prioritization, but not for the DDB method, using the total risk factor number. As shown in the figure, home and hospital buildings are at the same damage level in the DDB method (red painted-sign reflecting the heavy damage level). With use of the proposed fuzzy method, building damage of the two buildings is defined at 0.7 and the building occupancy type factors are 3 and 9 for home and hospital, respectively. Then, the indirect impact consequence factors are inputted at 0.0 and 1.0. Hence, the results of total risk score are 0.287 and 0.718 for home and hospital, respectively. For the garage and school buildings in which the school building contains higher damage but they are classified as the same yellow painted-sign or moderate damage. However, PFM can identify the damage levels of the two buildings with different damage scale as 0.3 for the garage and 0.5 for the school building.

Table 5.23 Example buildings with Total Risk Index

Building	Distinctive damage based	Fuzzy Application			
		Input data			Total Risk Index
		Damaged level	Indirect impact	Building Occ.	
Garage	Y	0.30	0.0	Res(3)	0.114
Government Office	Y	0.30	0.7	Gov(6)	0.309
Power Plant	Y	0.50	1.0	Gov(6)	0.500
School	Y	0.50	0.5	School(8)	0.375
Home	R	0.70	0.0	Res(3)	0.287
Hospital	R	0.70	1.0	Hos(9)	0.718

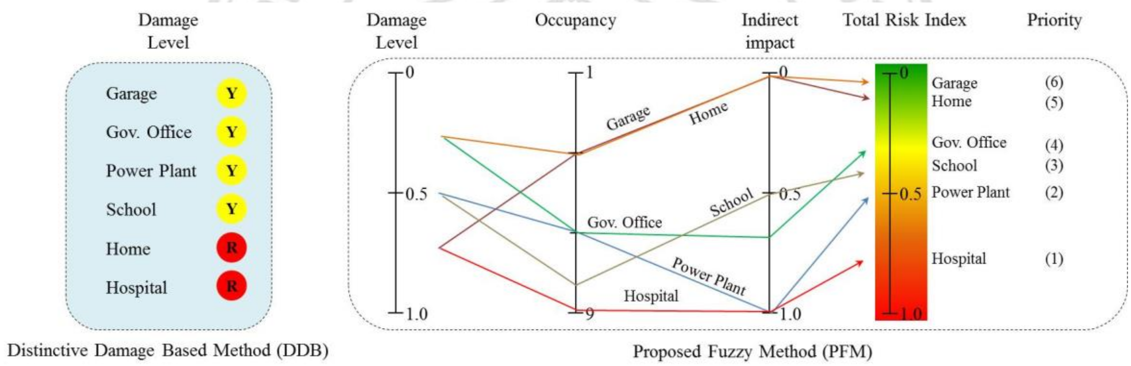


Figure 5.16 Applications of distinctive damage based method and proposed fuzzy method

From the application of the proposed fuzzy model (see in Table 5.23 and Figure 5.16), the hospital building is the first priority needed to repair with the total index of 0.718. The power plant building has damage level as severe as the school building. However, the power plant building, due to the higher indirect effect compared to the school building, has the total risk index of 0.500 which is higher than 0.375 of the school building. The building with less damage and low indirect impact; such as garage building has the total risk index of 0.114 which is identified as non-urgent to repair.

5.3 Artificial Neural Network Applications in Risk Model

Artificial neural networks (ANNs) are man-made systems that can perform some intelligent activities, similar to those of the human's brain. They can learn and acquire the knowledge about phenomenon and can also be trained to response to that phenomenon appropriately. Their quality of response improves, as they learn more and more. This characteristic of the artificial neural networks puts them in place between the conventional computational devices and human brain. This is reason that why, although, the fuzzy logic can encode expert knowledge using linguistic labels. But, it usually takes a lot of time to input the membership functions for every variable in each. Moreover, applications of fuzzy systems are restricted to the fields where expert knowledge is available and the number of input variables is small. With neural network learning technique, it can automate this process and reduce development time and cost while improve performance and extracting fuzzy rules from numerical data automatically (overcoming the fuzzy problem of knowledge acquisition), Effati *et al* (2014).

It has been found that the ANNs, specifically Multilayer Perceptron (MLP) model, has several advantages for this study. For example, it has the ability to handle imprecise and fuzzy information and the capability to analyze complex data patterns. Ability of learning is one of the most important characteristics of ANNs. This network consists of a number of interconnected nodes from all layers as shown in Figure 5.17.

In the MLP structure, the neurons are grouped in three layers. The first and last layers are called input and output layers respectively, because they represent inputs and outputs of the overall network. The remaining layers are called hidden layers. The number of the input nodes is equal to the number of the data sources. The number of output nodes is constrained by the application and the number of outputs. The number of hidden layers and the number of neurons in each layer depends on the architecture of the network. It is usually determined by trial and error. The network weights are modified in the training process by a number of learning algorithms based on back propagation learning, Vahidnia *et al* (2009).

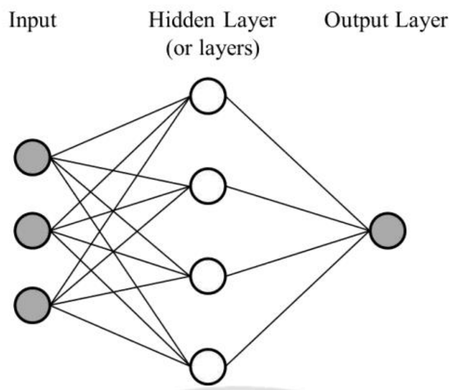


Figure 5.17 Structure of Multilayer Perceptron with one hidden layer

This section briefly explains the implementation steps of using the artificial neural network for the earthquake loss estimation. The basic procedures have six primary steps as:

1) Collection data
2) Create the network
3) Configure the network
4) Train the network
5) Validate the network
6) Use network

The collection data in step 1, the study area is located in the Chiang Rai Municipality Northern of Thailand. The area under investigated has total 79.3 km^2 with 46,775 buildings. Thus, the number of data sources is equal to 46,775 records including building information. In this research, the use of data was divided into the proportion of 70 to 30 for training data and testing respectively, as shown in Figures 5.18 – 5.19. Figure 5.19 shows the example data of Damage Risk Score was dividing into the proportion of 70 to 30 for training data and testing data. Figure 5.19 shows the example data of Total Risk Score was dividing into the proportion of 70 to 30 for training data and testing data, respectively.

Data input for ANNs model Output

70% Data for Training

Building ID.	Structure Type	RVS Score	PGA(g)	Damage Score
1	9	5.6	0.20	0.827
2	3	2.6	0.140	0.826
3	3	2.6	0.142	0.828
.	…	…	…	…
.	…	…	…	…
32743	3	1.1	0.169	0.984
.	…	…	…	…
.	…	…	…	…
46,775	3	2.6	0.159	0.946

30% Data for Testing

Structure Type

Where;

C1	= 1	URM	= 7
C2	= 2	W1	= 8
C3	= 3	W2	= 9
S1	= 4	W1C3	= 10
S2	= 5	W2C3	= 11
S3	= 6		

Figure 5.18 Example of data records for neural network Damage Risk Score

Data input for ANNs model Output

70% Data for Training

Building ID.	Structure Type	Occupancy	Damage Score	Total Risk Score
1	9	3	0.827	0.50
2	3	3	0.826	0.50
3	3	5	0.828	0.625
.	…	…	…	…
.	…	…	…	…
32743	3	1	0.984	0.375
.	…	…	…	…
.	…	…	…	…
46,775	3	9	0.946	0.962

30% Data for Testing

Occupancy Type

Where;

Emer. Serv.	= 9	Industrial	= 4
School	= 8	Residential	= 3
Historic	= 7	Office	= 2
Government	= 6	Commercial	= 1
Assembly	= 5		

Figure 5.19 Example of data records for neural network Total Risk Score

Create the network in step 2, the architecture of neural network is based on multilayer back propagation neural network. Figure 5.20 shows the architecture of the neural network of Damage Risk Score that containing 3 layers. The input layer has total 3 nodes that consist of the building type, PGA(g) and RVS score. In the hidden layer that consist of the synaptic weight, hidden nodes and bias. The output layer has a single node as the Damage Score. Figure 5.21 shows the architecture of the neural network of Total Risk Score that containing 3 layers. The input layer has total 2 nodes that consist of the Damage Score and building occupancy. In the hidden layer that consist of the synaptic weight, hidden nodes and bias. The output layer has a single node as the Total Risk Score.

In this study, the sigmoid transfer function was used in the hidden layers, while purelin was used for function fitting problems in the output layer.

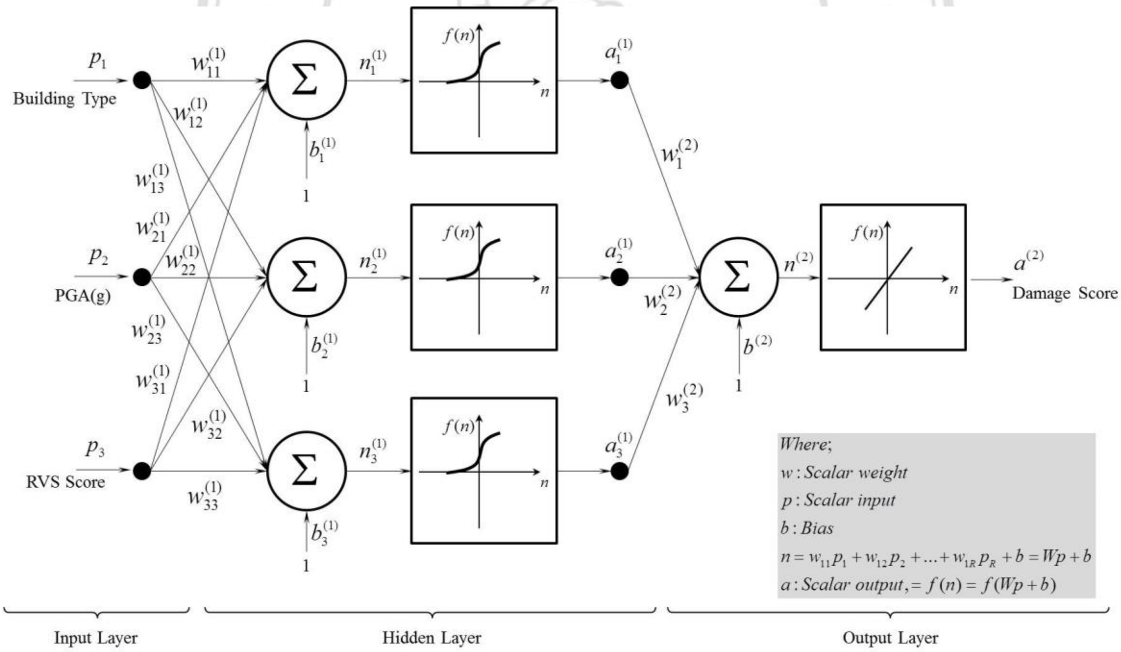


Figure 5.20 Proposed neuro structure of the Damage Score of building

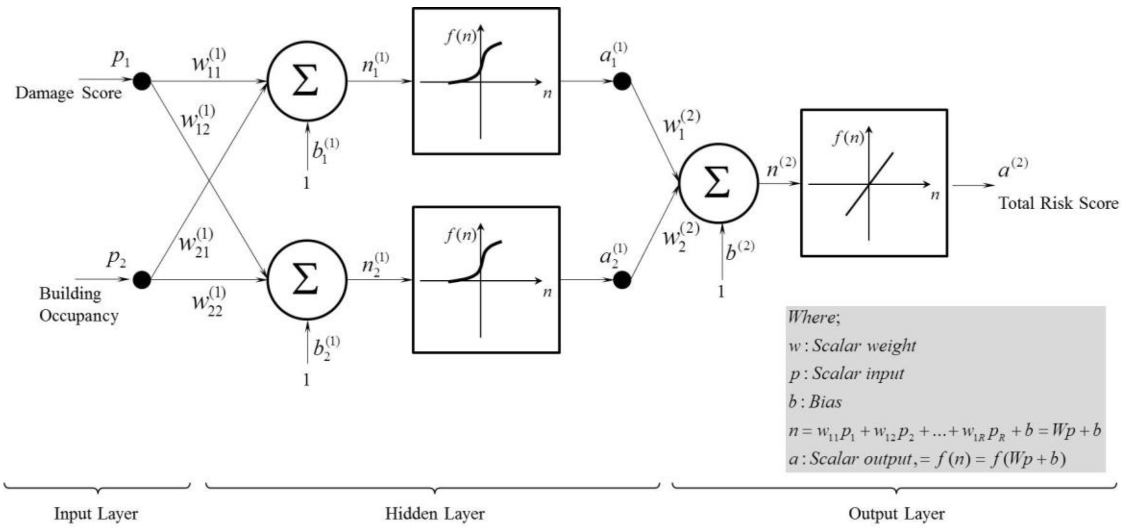


Figure 5.21 Proposed neuro structure of the Total risk score of building

Training process of this adaptive network is carried out in two steps, forward and backward. In the forward pass of the learning algorithm the process up to hidden layers. In the hidden layer, the consequent parameters are adjusted and the network output in final layer. In the backward pass, the error rates propagate backward and the premise parameters in hidden layer are updated.

Configure the Neural Networks in Steps 3, after the data has collected, the next step in training a network is to create the network object. This study contains a predefined set of input and target vectors. The input vectors define data regarding building information and hazard score. Target values define relative values of the Damage Score and Total Risk Score. The next step is to create the network with define testing of the number of cells in the hidden layers from 1 – (2n+1) and learning rate which produces excellent results.

Train and Apply Multilayer Neural Networks in Step 4, the process of training a neural network involves tuning the values of the weights and biases of the network to optimize network performance. The performance function for feedforward networks is Root Mean Square Error (RMSE) between the network outputs (a_i) and the target outputs (t_i).

$$RMSE = \left(\frac{1}{N} \sum_{i=1}^{N} (e_i)^2 \right)^{\frac{1}{2}} = \left(\frac{1}{N} \sum_{i=1}^{N} (t_i - a_i)^2 \right)^{\frac{1}{2}} \tag{5.1}$$

Where;

N = Total number of records

It is very difficult to know which training algorithm will be the fastest for a given problem as shown in Table 5.24.

Table 5.24 Training algorithm

Acronym	Algorithm	Description
LM	Trainlm	Levenberg-Marquardt
BFG	trainbfg	BFGS Quasi-Newton
RP	trainrp	Resilient Backpropagation
SCG	trainscg	Scaled Conjugate Gradient
CGB	traincgb	Conjugate Gradient with Powell/Beale Restarts
CGF	traincgf	Fletcher-Powell Conjugate Gradient
CGP	traincgp	Polak-Ribiere Conjugate Gradient
OSS	trainoss	One step secant
GDX	traingdx	Variable Learning Rate Gradient Descent

This depends on many factors, including the complexity of the problem, the number of data points in the training set, the number of weights and biases in the network, the error goal, and whether the network is being used for pattern recognition (discriminant analysis) or function approximation (regression). It is a variety of different architectures and complexities are used, and the networks are trained to a variety of different accuracy levels. In this study focus on trainlm performs better on function fitting problems also fastest training function. In many case, trainlm is able to obtain lower mean square errors than any of the other algorithms.

Validate the network in Step 5, when the training is completed its want to check the network performance and determine if any changes need to be made to the training process, the network architecture or the data sets. For validating the network is to create a regression plot, which shows the relationship between the outputs of the network and the targets. If the training were perfect, the network outputs and the targets would be exactly equal, but the relationship is rarely perfect in practice or indicates that there is an exact linear relationship between outputs and targets (R =1). If R is close to zero, then there is no linear relationship between output and targets.

Use network in step 6, after the network is trained and validated, the network object can be used to calculate the network response to any input. However, each time a neural network is trained, can result in different solution due to different initial weight and bias value and different divisions of data in to training, validation, and test sets. As a result, different neural networks trained on the same problem can give different outputs for the same input between output and targets. As explained in the previous sections (step 1-6). The methodology can presents in Figure 5.22.

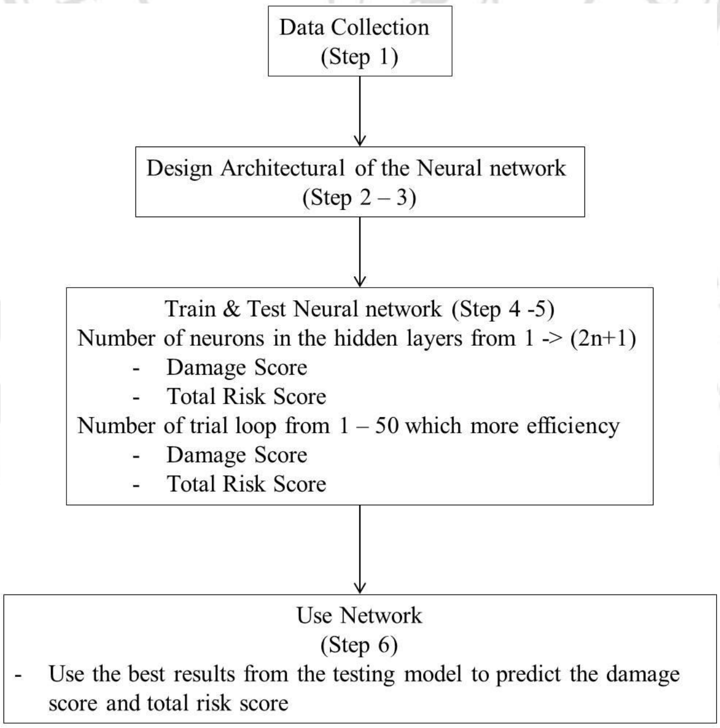


Figure 5.22 Research methodologies for identification of Damage Score and Total Risk Score

Figure 5.22 shows the research methodologies. It is proposed for identification of building Damage Score and Total Risk Score. This section identifies number of nodes in the hidden layers from 1 till (2n+1) where (n) is number of input factors. Example, in Figures 5.20 – 5.21 there were 3 and 2 input factors, respectively. Therefore, trial hidden node from 1 – 7 nodes and 1 – 5 nodes for more efficiency in damage score and total risk score, respectively. The neural network analysis of hidden node with training and testing data can be expressed in Figures 5.23 – 5.26.

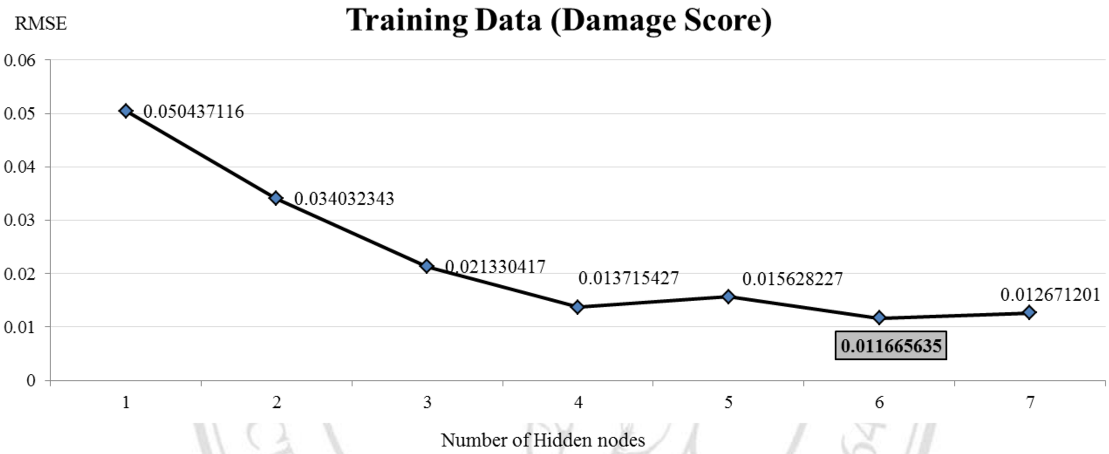


Figure 5.23 Result of neural network analysis of hidden nodes in Training data for damage score, Trial from 1 till (2n+1) nodes

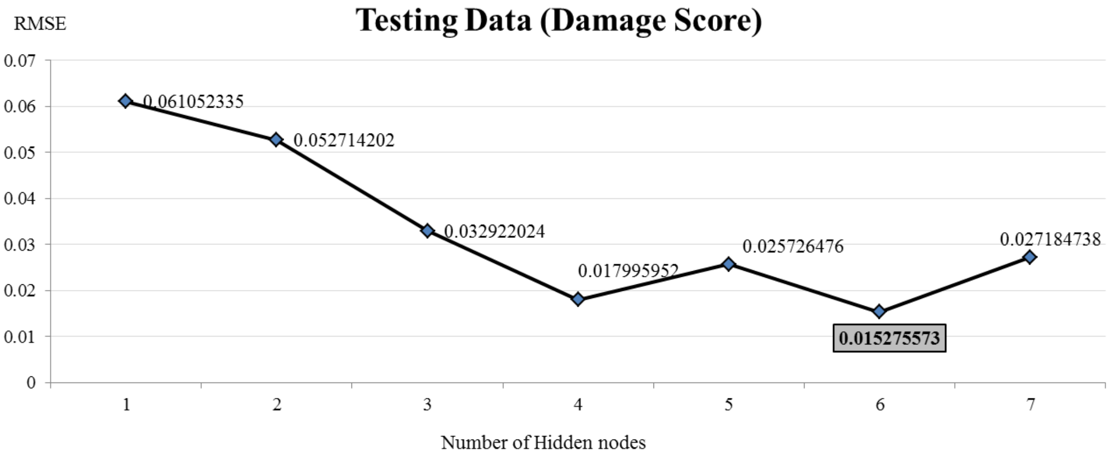


Figure 5.24 Result of neural network analysis of hidden nodes in Testing data for damage score, Trial from 1 till (2n+1) nodes

With training data and testing data of damage score, it was found that the 6 hidden nodes (or 2n nodes) minimize RMSE number equal to 0.0117 and 0.0153, respectively.

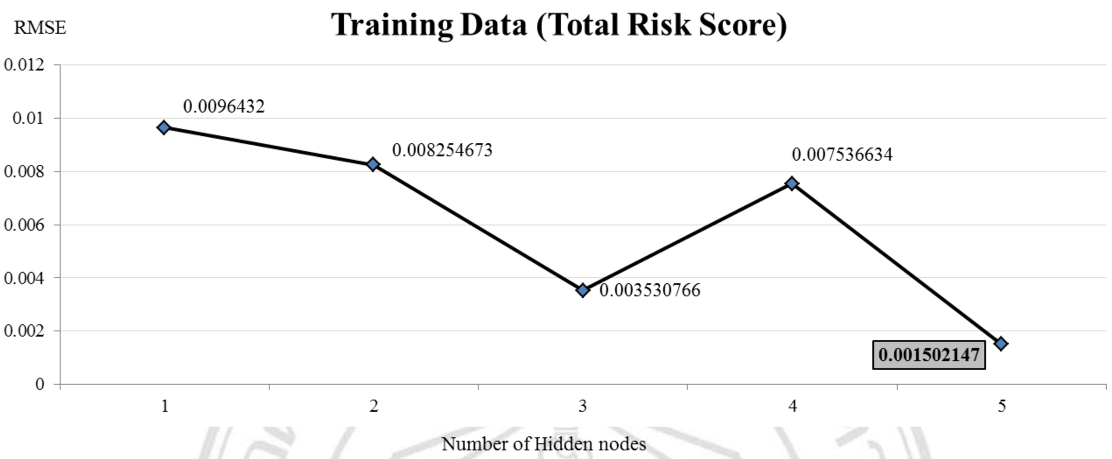


Figure 5.25 Result of neural network analysis of hidden nodes in Training data for Total Risk score, Trial from 1 till (2n+1) nodes

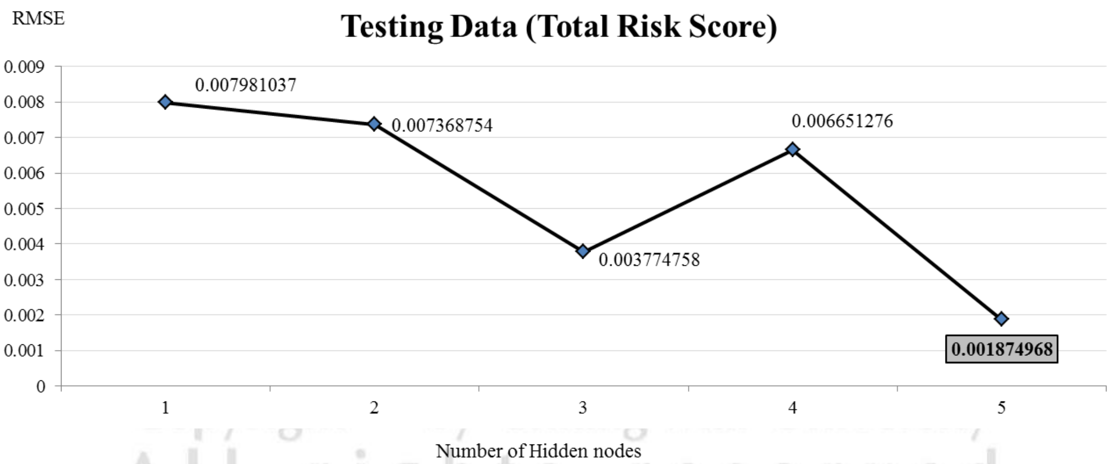


Figure 5.26 Result of neural network analysis of hidden nodes in Testing data for Total Risk score, Trial from 1 till (2n+1) nodes

From Figure 5.25 and 5.26, the training data and testing data of Total risk score, it was found that the 5 hidden nodes (or 2n+1 nodes) minimize RMSE number equal to 0.0015 and 0.0019, respectively.

The results of comparison learning process showed that 6 hidden nodes is effective for the prototype of Damage Score, and 5 hidden nodes is effective for the prototype of Total Risk Score. Moreover, number of loop also affects the performance of the model. Therefore, to finding a suitable number of loops the trial test results can express in Table 5.25 and Figure 5.27.

Table 5.25 Root mean square error (RMSE) result from loops test

Number of hidden node	Number of Run (loop)									
	1-5	1-10	1-15	1-20	1-25	1-30	1-35	1-40	1-45	1-50
1	0.0505	0.0504	0.0504	0.0504	0.0504	0.0504	0.0504	0.0504	0.0504	0.0504
2	0.0480	0.0404	0.0305	0.0269	0.0295	0.0269	0.0339	0.0269	0.0339	0.0269
3	0.0442	0.0330	0.0241	0.0226	0.0211	0.0218	0.0211	0.0149	0.0149	0.0149
4	0.0404	0.0177	0.0153	0.0200	0.0169	0.0146	0.0146	0.0192	0.0146	0.0146
5	0.0455	0.0191	0.0173	0.0159	0.0128	0.0202	0.0154	0.0128	0.0128	0.0128
6	0.0293	0.0189	0.0097	0.0184	0.0125	0.0135	0.0099	0.0097	0.0131	0.0131
7	0.0292	0.0177	0.0152	0.0140	0.0134	0.0131	0.0120	0.0115	0.0114	0.0240
Average	0.0410	0.0282	0.0232	0.0240	0.0224	0.0229	0.0225	**0.0208**	0.0216	0.0224

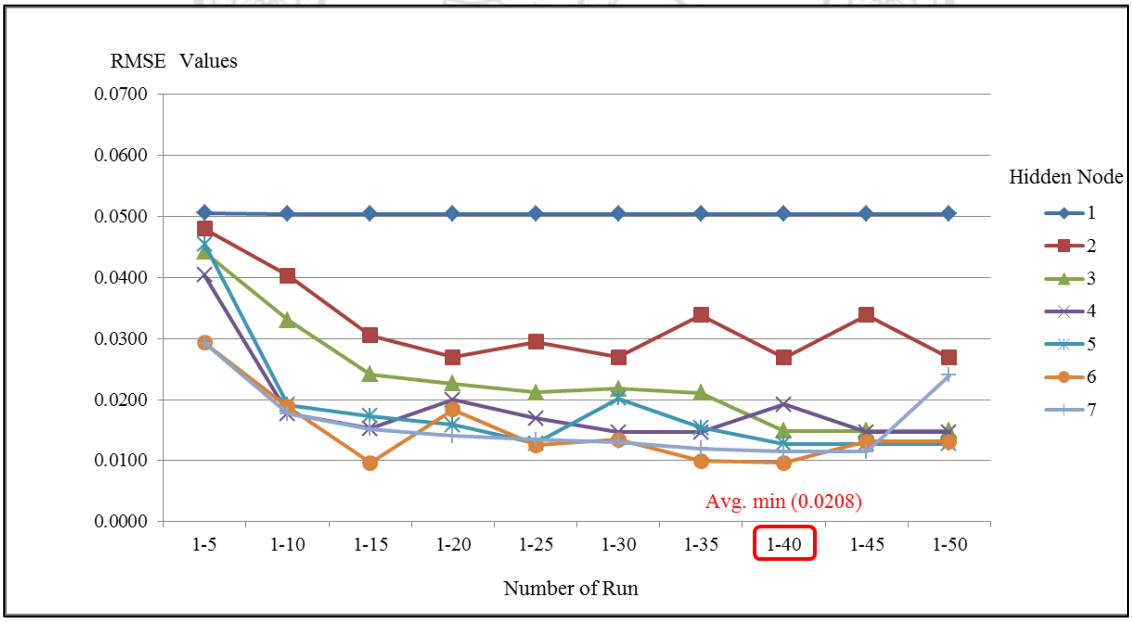


Figure 5.27 Loops test for damage score

The experiment in hidden node from 1 till 2n+1 nodes showed that the suitable loops number for Damage Score model is 40. It minimizes average RMSE values equal to 0.0208. In the following sections, suitable numbers of loops for total risk score can express in Table 5.26 and Figure 5.28.

Table 5.26 Root mean square error (RMSE) result from loops test

Number of hidden node	Number of Run									
	1-5	1-10	1-15	1-20	1-25	1-30	1-35	1-40	1-45	1-50
1	0.0161	0.0096	0.0096	0.0096	0.0096	0.0096	0.0096	0.0096	0.0096	0.0096
2	0.0402	0.0094	0.0091	0.0089	0.0007	0.0086	0.0084	0.0083	0.0094	0.0083
3	0.0101	0.0090	0.0081	0.0078	0.0037	0.0072	0.0051	0.0045	0.0064	0.0068
4	0.0093	0.0089	0.0022	0.0087	0.0087	0.0078	0.0081	0.0081	0.0091	0.0076
5	0.0091	0.0078	0.0075	0.0061	0.0086	0.0089	0.0078	0.0039	0.0089	0.0083
Average	0.0170	0.0089	0.0073	0.0082	**0.0062**	0.0084	0.0078	0.0069	0.0087	0.0081

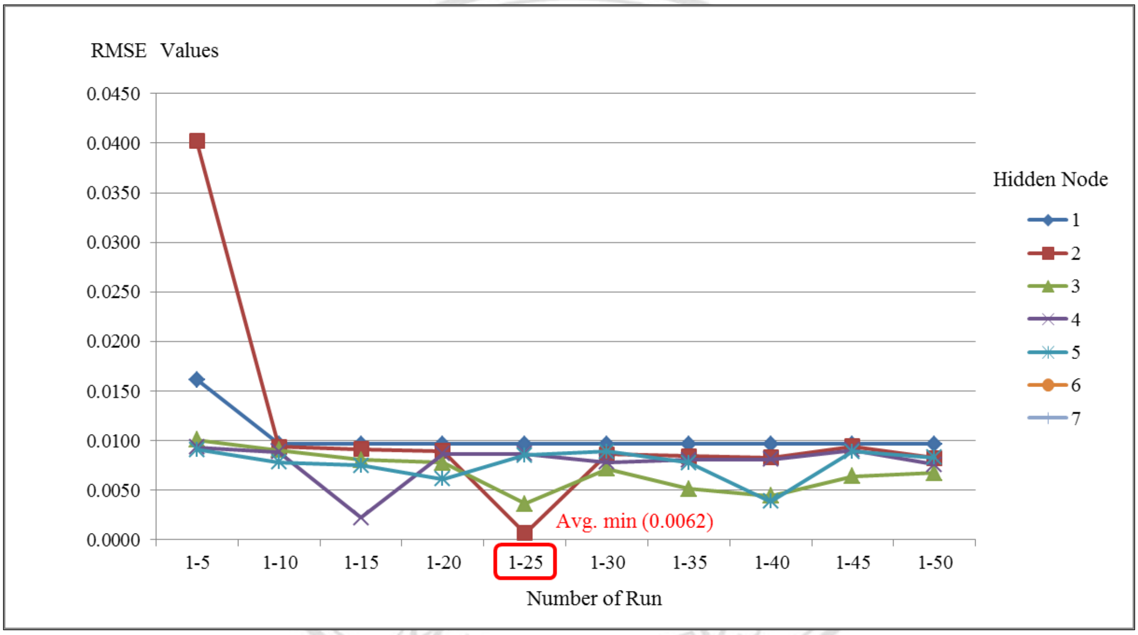


Figure 5.28 Loops test for Total Risk Score

The experiment in hidden node from 1 till 2n+1 nodes showed that the suitable loops number for Total Risk Score model is 25. It minimizes average RMSE values equal to 0.0062.

In the previous sections the results of comparison learning model. The results use in the model to predict Damage Score and Total Risk Score. Figures 5.29 – 5.33 show the spatial data from damage score and total risk score with 70% of total records used in learning neural network.

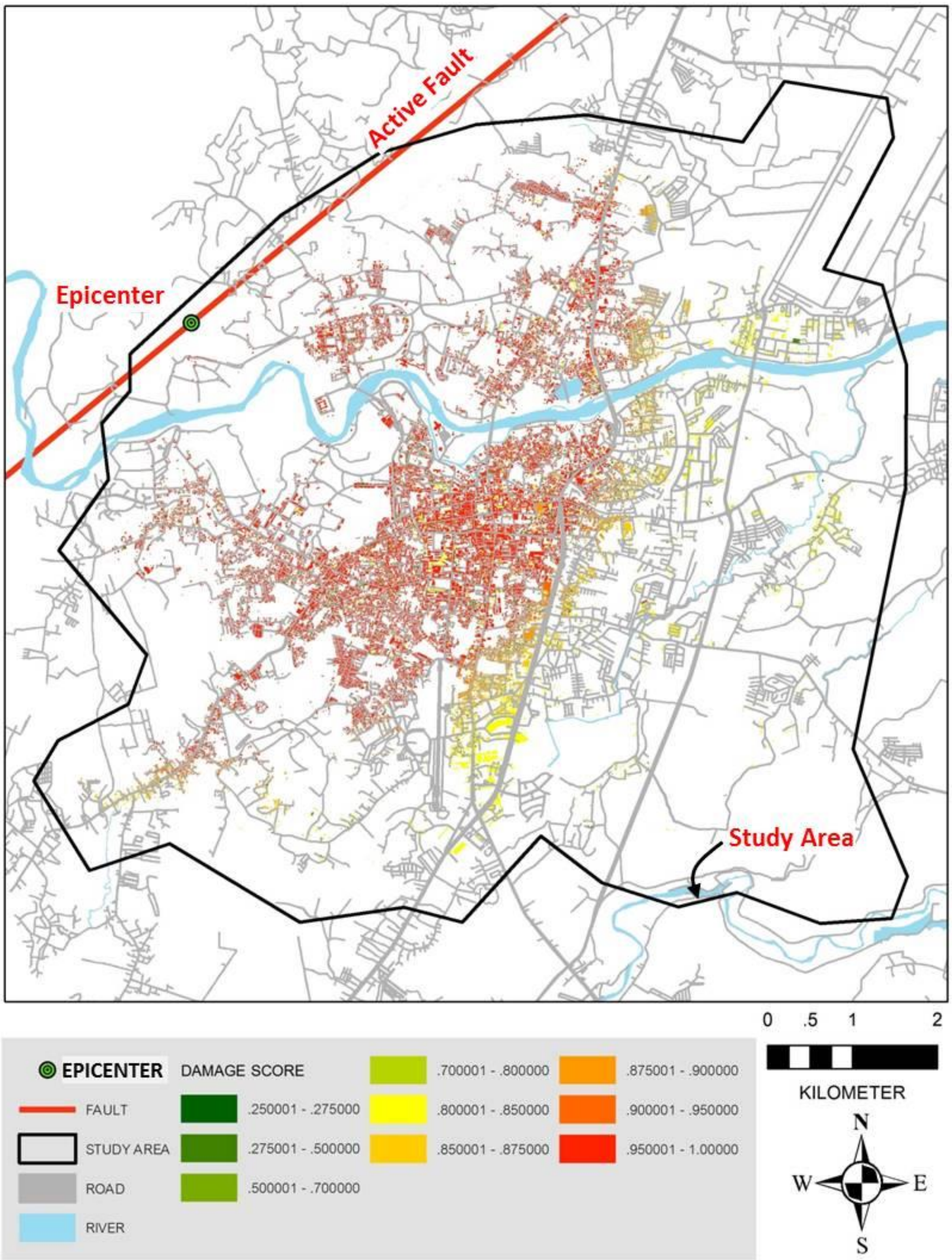


Figure 5.29 Spatial records of Damage Score for data training in neural network

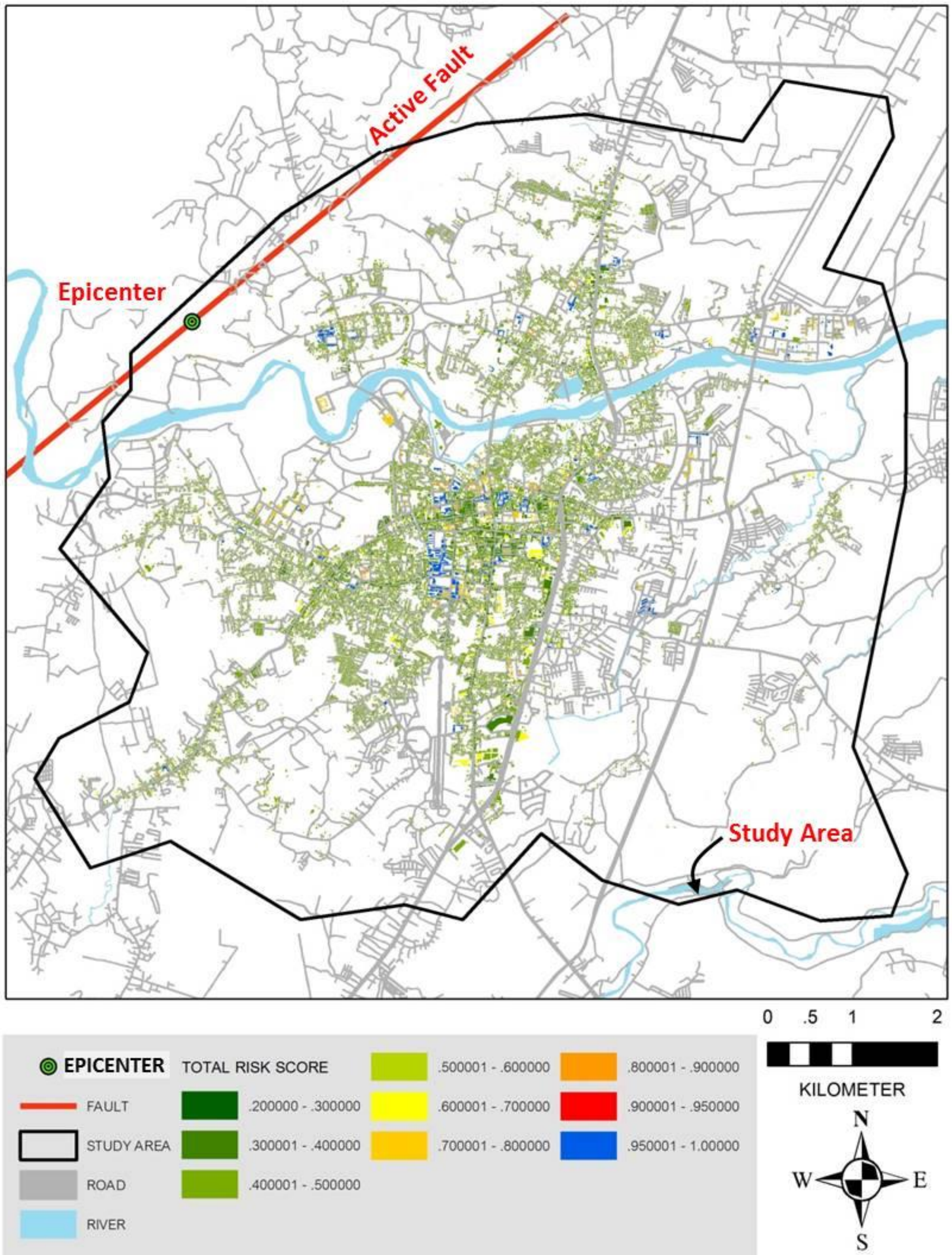


Figure 5.30 Spatial records of Total Risk Score for data training in neural network

Figures 5.31 – 5.32 show the spatial results. They are the 70% neural network training data and 30% predicted buildings (or 30% of total records) for damage score and total risk score. The RMSE values are 0.0145 and 0.0083, respectively.

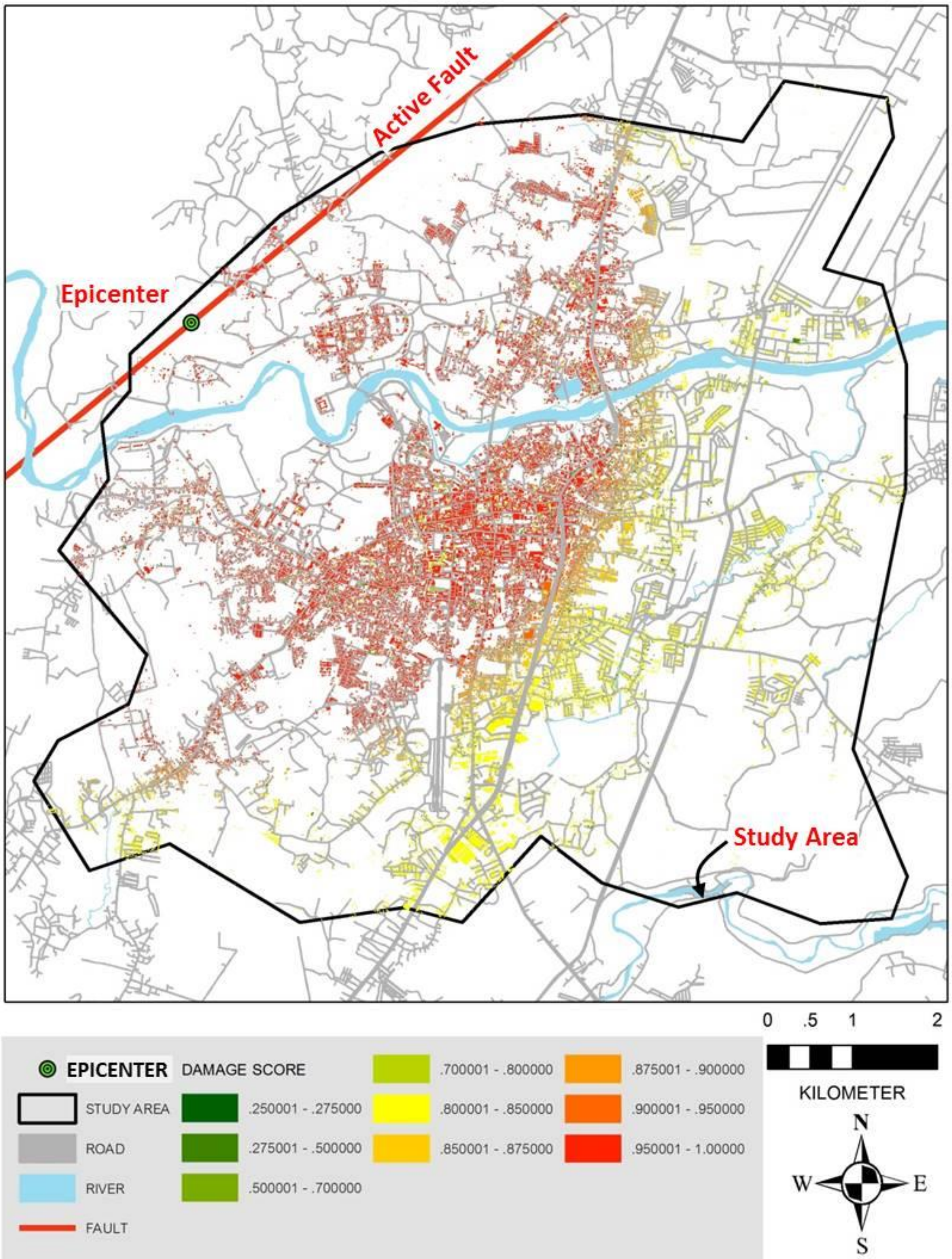


Figure 5.31 Spatial results of Damage Score from neural network testing model

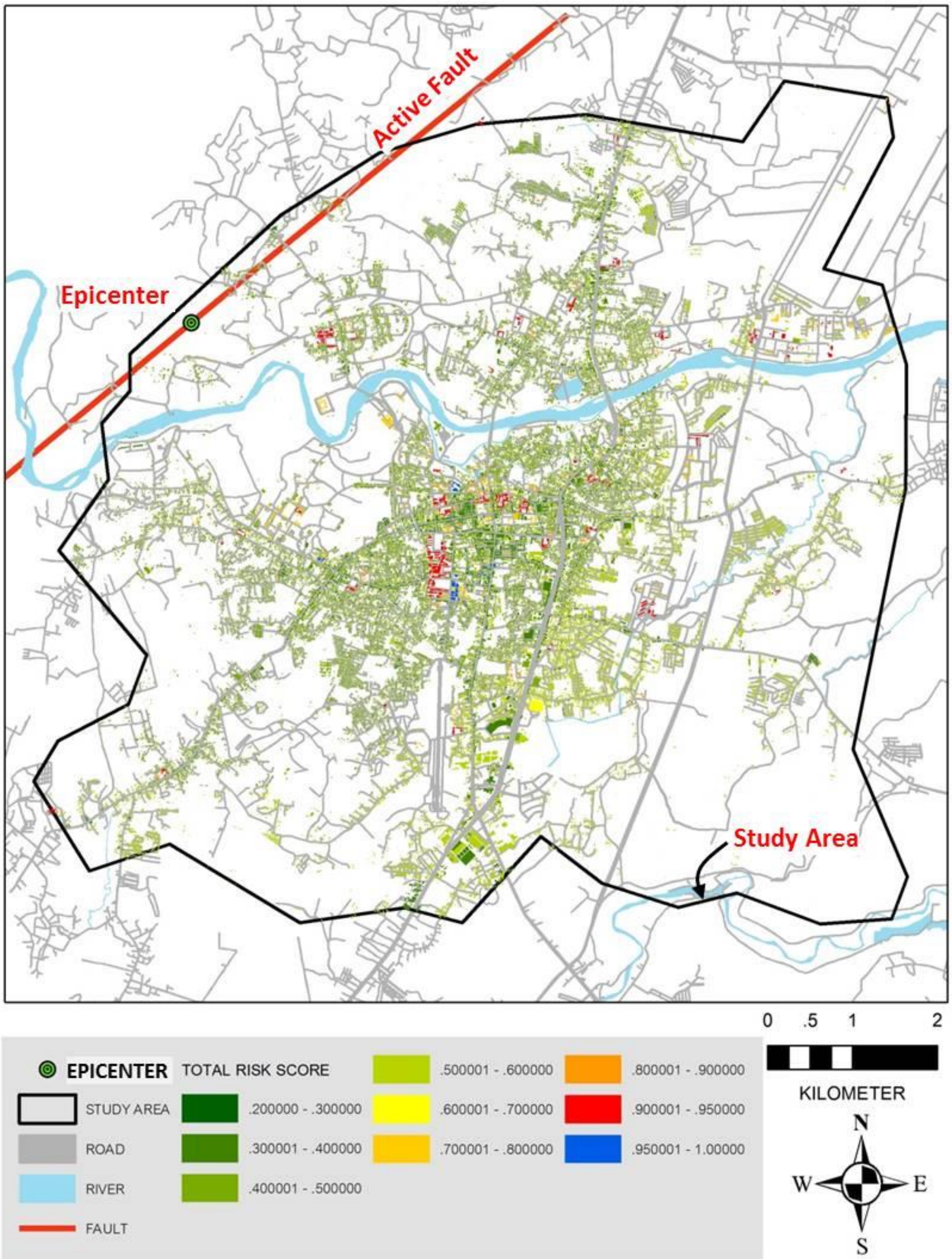


Figure 5.32 Spatial results of Total Risk Score from neural network testing model

The earthquake is natural disasters which damage to life and property of the people highly, and Thailand has many seismic risk areas, therefore the study about methodology to prediction hazard area with risk mitigation by prioritize building to retrofit so needed. The study has objectives to apply Geo-Informatics Technology and

Artificial Neural network in predicting the seismic hazard area and building retrofit in Chiang Rai Municipality. The research methodology included development of the fundamental Artificial Neural Network learning procedure of Levenberg – Marquardt method (LM) with neural network architecture is based on a multilayer feed-forward back-propagation learning algorithm that has single output. With number of cells in the hidden layers from 1 till (2n+1) were used from the best results in testing model to predictions damage score and total risk score in Chiang Rai Municipality. Figures 5.31 - 5.32 depict the output of applying neural network to forecast on the study area for identification of building with high risk to damage and which buildings that need to be extremely concentration. The study found that gave an accurate forecast which gave the RMSE values of damage score and total risk score equal to 0.0145 and 0.0083, the standard accepted value are nearly 0.0 and so show that the forecast accuracy is highly reliable.