The Use of Artificial Neural Networks to Prioritize Impact Factors Affecting Thai Rural Village Development

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Abstract: This paper aims to prioritize impact factors which affect Thai rural village development. The basic village-levelled information database (NRD-2C) of the Community Development Department (CDD), Ministry of Interior, Thailand, was applied with Artificial Neural Networks (ANN) to measure the amount of impact for each factor affecting Thai rural village development. According to results, the top 5 impact factors are “Land Possession”, “Electricity”, “Communication”, “Educational Level”, and “Household Industry” with 17.88, 15.35, 14.02, 12.06, and 10.57 score of impact respectively with 95.60 percent of estimated accuracy.

Keywords: *Prioritization, Rural Development, Community Development, Artificial Neural Networks*

1. Introduction

Human beings have known and learned the development of livelihood since they were born on the earth. As many evidences discovered so far, there have been the evolution of tools, constructions, weapons, clothes, vehicles, etc. Furthermore, much beliefs and teachings of Roman, Greek, Arabic, Chinese, Indian philosophers have been accepted and spread worldwide. So that “Development” has become a science and been adapted into many areas of study. Development has been a key to solve economic crisis such as inflation, economic recession, and unemployment. The Community Development Department of Thailand was established in 1962 under the Ministry of Interior to coordinate with all governors, CDD workers, community leaders and people for collecting community data in rural areas, then analyzing data, reporting useful information and making policies for community development. Community planners and developers have been persistently concerned with building the good community (Grant, 2006).

There are 2 types of Thai rural community database; BMN (Basic Minimum Needs), household-levelled information, and NRD-2C (Basic Village Information), village-levelled information. BMN covers approximately 8 million rural households and is updated every year, and NRD-2C covers 69,763 villages in rural area of Thailand and will be updated every 2 years (Community Development Department, 2007). In this study, only NRD-2C was used to measure the amount of impact of each factor.

Figure 1: NRD-2C Database Overview in 6 Categories

Source: Reproduced from Community Development Department (2003), (NRD2C)

NRD-2C Database contains 31 key performance indicators (factors/variables) which are classified into 6 categories as shown in Figure 1 e.g. 1) Infrastructure, 2) Employment, 3) Public Health, 4) Education, 5) Community Strength, and 6) Natural Resources. So far, CDD has analyzed these databases with only a conventional quantitative analysis. They have only used a Statistical Distribution Analysis to describe and

classify the development level of villages in Thailand. Then prioritize these factors by using the numbers of villages which failed in each factor. The result is displayed in Table 1 below.

Table 1: A Summary of Factor Prioritization Affecting Thai Rural Development using Statistical Frequency Distribution Analysis (All Categories)

Rank	Factor	Total Villages Which Failed (Villages)
1	Learning by A Community	40,601
2	Sports	36,033
3	Soil Quality	20,849
4	Access of A Community's Financial Capital	16,312
5	Being Educated	15,547
6	Products from Other Agriculture	10,758
7	Water for Agriculture	8,502
8	Getting A Job	7,885
9	Products from Farms	7,450
10	Land Possession	5,847
11	Products from Rice	4,605
12	Water Quality	4,561
13	Social Protection	4,453
14	Further Studying beyond Limitation (Grade 9)	3,958
15	Environment Management	3,459
16	People Assembly	3,048
17	Community Participation	2,972
18	Road	2,817
19	Communication Technology Access (TV, Radio, Internet)	2,593
20	Water for Drinking	2,593
21	Household Industry	2,341
22	Working in Establishment	1,949
23	Educational Level	1,851
24	Water for Consumption	1,815
25	Benefits from Tourist Attraction	1,642
26	Electricity Access	995
27	Work Safety	982
28	Afforesting	849
29	Contagious Disease Prevention	829
30	Free from Addictive Drug	279
31	Land Utilization	2

But in term of impact evaluation, it is not necessary that the impact factor which most number of villages fail in has the most influence on Thai rural village development. On the other hand, the impact factor which has the most influence on Thai rural village development might have fewer number of failing villages. Moreover, all raw data in NRD-2C database were recorded as nominal data type (passed or failed), and the data of village development level were as ordinal data type (level 1, 2, and 3). By Technically, Correlation Analysis and Regression Analysis cannot be used to measure the amount of relationship or weight of impact. Previous studies done by West, Brockett, and Golden (1997); Thieme, Song, and Calantone (2000); Song and Zhao (2004) showed that Artificial Neural Networks (ANN) approach was well suited to complex relationships analysis and well dealt with all data types. It was found that ANN was used to evaluate general relationship quality (Bejou, Wray, and Ingram, 1996). So in this study, ANN was applied to measure the weight of impact for each factor.

2. Artificial Neural Networks (ANN)

ANN was applied in two stages: learning and testing. In the learning stage, a set of connection weights was calculated for a given set of input and output values. For back-propagation method, the output set

contained previously known values. An algorithm called the delta-learning rule was used to adjust the weights at the end of iterations until the output was more similar to the pre-defined output. Learning was complete when the network had learned the relationship between the inputs and outputs. During the learning, setting the number and the size of the hidden neurons was difficult. Hidden layers represented non-linearity or interactions between variables. The more complex interactions, the more hidden neurons were required. In the testing stage, weights calculated during the learning stage were engaged to estimate a new set of output for a given set of input values (Yesilyaprak, 2004) for measuring the estimated accuracy of the analysis.

Figure 2: Basic ANN Structure

Source: Reproduced from Giudici (2003)

Basically, a generic neuron j , with a threshold θ_j , received n input signals $x = [x_1, x_2, \dots, x_n]$ from the units to which it was connected in the previous layer. Each signal was attached with an importance weight $w_j = [w_{1j}, w_{2j}, \dots, w_{nj}]$. The combination function is usually linear; hence the potential was a weighted sum of the input values multiplied by the weights of the respective connections. This sum was compared with the value of the threshold. The potential of neuron j (p_j) was defined by the following linear combination:

$$p_j = \sum_{i=1}^n (x_i w_{ij})$$

3. Methodology

In this paper, it was assumed that all factors were related to the level of village development. So that all 31 factors were selected as the independent variables and the level of village development as the dependent variable as shown in Figure 3. Then ANN was applied to measure the weight/amount of impact, called “importance”, for each independent variable affecting the level of rural village development.

Figure 3: Conceptual Framework

Back-propagation algorithm was selected as a main approach of ANN and it was set to run continually and re-process as looping until the expected accuracy was not less than 95%, and then the analysis process was stopped. Once the weights of impact for each independent variable were retrieved. Then prioritized all of the weights of impact in descending order. The highest weight/importance was ranked 1st, and the lowest weight/importance was 31st.

4. Results

Table 2: A Summary of Factor Prioritization Affecting Thai Rural Development by Artificial Neural Networks (All Categories)

Factor Ranked by Impact	Factor Name	Score of Impact
1	Land Possession	17.88
2	Electricity Access	15.35
3	Communication Technology Access (TV, Radio, Internet)	14.02
4	Educational Level	12.06
5	Household Industry	10.57
6	People Assembly	10.55
7	Soil Quality	7.56
8	Community Participation	7.14
9	Water for Drinking	6.17
10	Contagious Disease Prevention	5.68
11	Getting A Job	5.68
12	Work Safety	5.53
13	Learning by A Community	4.93
14	Being Educated	4.64
15	Road	4.57
16	Water for Consumption	4.50
17	Sports	4.09
18	Access of A Community's Financial Capital	3.88
19	Water for Agriculture	3.73
20	Water Quality	1.76
21	Afforesting	1.40
22	Environment Management	1.30
23	Free from Addictive Drug	1.21
24	Social Protection	1.15
25	Products from Farms	1.06
26	Products from Other Agriculture	1.02
27	Land Utilization	0.95
27	Products from Rice	0.95
29	Benefits from Tourist Attraction	0.88
30	Working in Establishment	0.69
31	Further Studying beyond Regulation (Over Grade 9)	0.58

Estimated Accuracy: 95.60 % from ANN, Input Layer: 31 neurons, Output Layer: 1 neuron

5. Conclusion and Recommendations

Referring to Table 2, the factor which has the most impact to Thai rural village development is “Land Possession” (17.88%), the first runner-up is “Electricity” (15.35%), the second runner-up is “Communication” (14.02%), the third runner-up is “Educational Level” (12.06%), and the forth runner-up is “Household Industry” (10.57%). “Land Possession” has played the most important role in Thai rural development. This suggests that Thai government should keep on providing the title deeds or certificates of land ownership for agriculture to poor people in rural areas by Agricultural Land Reform Office (ALRO) established in 1975. Moreover ALRO has worked on this mission until present.

Furthermore, when consider “Natural Resources and Environment Category”, “Soil Quality” has significantly more impact to Thai rural development than others. This corresponds to “Land Possession”, the 1st rank. It seems that the government should make policies for people to possess their land first. Because the findings show that it is more important than the quality of soil improvement and land utilization. The 2nd and 3rd impact factors, “Electricity Access” and “Communication Technology Access”, which are related to information systems and technology, have slightly less impact. It seems likely that

the information and communication technology (ICT) nowadays play a very important role in developing rural areas as well as urban areas. ICT helps provide useful information, news and knowledge to people which are the key capital of community development. So it seems very worth for the government to keep investing in ICT for covering all areas of Thailand.

The 5th, 6th, 8th and 11th impact factors, “Household Industry”, “People Assembly”, “Community Participation”, and “Getting a Job”, are classified into “Employment Category” mixed with “Community Strength Category”. This finding could guide the government to promote grouping and participating of people and support them to make their household goods/products or jobs at the same time for earning their living. Owing to “Educational Level” is ranked 4th. So the government should pay more attention to educational policies to continually support and gain people’s opportunities and accesses into all supported educational systems.

From the study, the findings show that 2 methods of prioritization referred in this study, either Statistical Frequency Distribution Analysis or ANN gives different results and different views. Statistical Frequency Distribution Analysis shows the number of villages which passed and failed. On the other hand, ANN shows how much impact of each factor. From now, the government or a policy maker should consider these results both in term of frequency and impact. Some problems might have been found in many villages (high frequency), but they have caused small impact to those villages. In contrast, some problems might have been rarely found (low frequency), but they have caused much impact to those villages.

Suggestions for Future Studies: A next researcher might change the database, the independent variable, or the dependent variable for extracting meaningful knowledge or try to use different ranking methods to compare the results with this method.

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