ALKIRE-FOSTER ORIENTED ENSEMBLE FUZZY INFERENCE SYSTEM FOR URBAN POVERTY CLASSIFICATION

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To my beloved parents,

ZAKARIA BIN HJ YAHAYA

MAHANOM BINTI HJ SHARIF

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"In the name of Allah, the most Gracious and the most Merciful"

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ABSTRACT

Malaysia is a developing country which relies on the monetary approach to measure poverty. The approach is simple to measure but it is insensitive towards changes of the poor in multiple dimensions such as education, health and living standards especially in urban areas. Several current issues in classifying the urban poor include rigid dichotomy of the poor and non-poor, unable to capture changes that happens in various sub-groups of urban poor population and misclassified poverty indicators. This study developed a multidimensional poverty measurement framework which integrated i) Alkire-Foster approaches in quantification of multidimensional urban poor, ii) Adaptive Neural Fuzzy Inference Systems (ANFIS) to predict classification of urban poor and resolve the misclassification of urban poor and iii) ensemble ANFIS. 300 questionnaires were distributed to targeted households in Bandar Tasik Selatan, Kuala Lumpur. This study started with a comparison of data-driven Fuzzy Rule-Based System (FRBS) with the domain expert comprising FRBS classification. Next, the Alkire-Foster method was introduced which included parameter selection, dual cut off identification and aggregation of the poor. Then, the ANFIS prediction was carried out using various ANFIS combination models such as Genfis 1, Genfis 2 and Genfis 3 to predict the classification of urban poor. This study proceeded to improve the classification by proposing the ensemble ANFIS that included ensemble weighting and ensemble integration method. The performance of this proposed framework was evaluated using Root Mean Square Error (RMSE), Mean Square Error (MSE), and R-Squared. For validation purposes, this study was reviewed by officers at the Zakat Collection Centre, Kuala Lumpur as the domain experts. The findings showed that the Genfis 3 using Fuzzy C-Means clustering algorithm in ANFIS outperformed all the ANFIS models, by obtaining the least MSE and RMSE values and highest R-Squared. These results included the Health dimension which was excluded in the current poverty measurement. Overall, this study has managed to address the urban poor classification by providing multiple dimensions of the poor and produce robust prediction results.

ABSTRAK

Malaysia adalah sebuah negara yang bergantung kepada pendekatan kewangan apabila dikaitkan dengan pengukuran kemiskinan. Pendekatan kewangan semasa adalah lebih mudah untuk diukur, namun ianya tidak sensitif kepada perubahan kemiskinan bagi pelbagai dimensi kemiskinan termasuk pendidikan, kesihatan dan taraf hidup. Beberapa isu semasa di dalam mengklasifikasikan miskin bandar termasuklah pembahagian yang ketat untuk miskin dan bukan miskin, kegagalan untuk mengenalpasti perubahan yang berlaku di pelbagai subkumpulan miskin bandar dan pengkelasan petunjuk kemiskinan yang salah. Kajian ini mencadangkan rangka kerja pengukuran kemiskinan multidimensi yang mana merangkumi tiga bahagian, mengintegrasi i) pendekatan *Alkire-Foster* dalam pengiraan miskin bandar dalam multidimensi, ii) *Adaptive Neural Fuzzy Inference Systems* (ANFIS) dalam meramalkan pengkelasan miskin bandar; dan menyelesaikan masalah tersalah klasifikasi miskin bandar dengan menggunakan iii) "*ensemble ANFIS*". Sebanyak 300 soal selidik telah diedarkan kepada isi rumah yang disasarkan di kawasan urban di Bandar Tasik Selatan, Kuala Lumpur. Kajian ini dimulakan dengan "*Fuzzy Rule-Based System (FRBS)*" berasaskan data, dengan membanding beza klasifikasi daripada ahli domain dan juga FRBS. Kemudian, kaedah "*Alkire-Foster*" diperkenalkan, dengan pemilihan parameter, identifikasi pemotongan berganda dan pengagregatan kumpulan miskin menjadi antara kaedah yang terlibat. Kemudian disusuli dengan peramalan ANFIS menggunakan pelbagai model kombinasi ANFIS iaitu Genfis 1, Genfis 2 dan Genfis 3 untuk meramalkan klasifikasi miskin bandar. Kajian ini diteruskan dengan menambahbaik pengkelasan dengan mencadangkan "*ensemble ANFIS*" dengan menggunakan *ensemble* pemberat dan *ensemble* integrasi. Prestasi rangka kerja yang dicadangkan ini dinilai dengan menggunakan Ralat Kesilapan Punca Kuasa (RMSE), Ralat Panjang Persegi (MSE) dan R-Kuasa Dua. Untuk tujuan pengesahan, kajian ini telah melalui ahli domain iaitu pegawai dari Pusat Pungutan Zakat. Keseluruhannya, keputusan kajian ini mencatatkan Genfis 3 yang menggunakan algoritma "*Fuzzy C-Means*" yang terbukti mengalahkan model ANFIS yang lain, dengan nilai MSE dan RMSE yang paling rendah dan R-Kuasa Dua yang paling tinggi. Selain itu, keputusan kajian turut memasukkan dimensi Kesihatan yang dikeluarkan dari penilaian kemiskinan semasa. Keseluruhannya, kajian ini berupaya untuk mengenalpasti pengkelasan miskin bandar dengan menyediakan pelbagai dimensi kemiskinan dan menghasilkan jangkaan keputusan yang bagus.

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LIST OF ABBREVIATIONS

ANFIS	-	Adaptive Network-based Fuzzy Inference System
ANN	-	Artificial Neural Network
API	-	Air Pollution Index
CART	-	Classification and Regression Tree
FCM	-	Fuzzy C-Means
FGT	-	Foster-Greek-Thorbecke
FIS	-	Fuzzy Inference System
FRBS	-	Fuzzy Rule-based System
HES	-	Household Expenditure Survey
HPI	-	Human Poverty Index
MDGR	-	Millennium Development Goals Report
MFs	-	Membership Functions
MPI	-	Multidimensional Poverty Index
MSE	-	Mean Square Error
MYR	-	Malaysian Ringgit
NEP	-	New Economic Policy
PCA	-	Principal Component Analysis
PLI	-	Poverty Line Income
RAM	-	Random Access Memory
RF-CART	-	Random Forest Classification and Regression Tree
RMSE	-	Root Mean Square Error
VEP	-	Visual-Evoked Potential

CHAPTER 1

INTRODUCTION

1.1 Problem Background

Malaysia has experienced tremendous economic development in recent years, as it gears towards becoming a fully industrialised nation by the year 2020. Primarily, poverty has only been associated with rural phenomena and is biased agriculturally. This is due to rural household involvement in small-scale agricultural production. Although poverty alleviation strategies in Malaysia have been recognised as an acclaimed success by the United Nations, new forms of poverty have emerged in urban areas as a result of rapid economic growth and development. Extensive poverty studies in Malaysia have previously focused on the poverty line and evaluation particularly in rural communities (Solaymani and Kari, 2014; Hatta and Ali, 2013; Nawai and Duasa, 2009). However, several researchers have also highlighted the incidence of relative poverty studies in Malaysia (Lazim, 2010; Lazim and Osman, 2009) using macro data released by the Economic Planning Unit, which is a major large-scale data source for the country. There are also poverty studies based on smaller datasets, e.g. studies on poverty in individual cities (Samat et *al*., 2012; Othman et *al*., 2010). During the Asian Financial Crisis in 1997, the Malaysian economy suffered a high rate of unemployment, hence income and wealth inequality also worsened. Consequently, poverty emerged as an urban phenomenon despite being predominantly eminent in rural areas. Hence, there are numerous studies that local scholars have conducted that highlight urban poverty (Tarmizi *et al*., 2014; Shiraishi, 2014; Yusof, 2012; Zainal *et al.*, 2012, Mok *et al*., 2007).

According to Belhadj (2010), poverty and welfare can be defined using welfarist and non-welfarist approaches. The standard welfarist approach uses the money metric measure, which assesses the minimum consumption levels for survival, while the non-welfarist approach focuses on the multiple dimensions of society. However, the monetary aspect often lacks the provision of deprivations in other dimensions. Too focusing on monetary aspects results in false assumptions of the consumption poor people, that they are almost the same level as those who suffer malnutrition, are ill educated, or are disempowered. On the other hand, the multidimensional poverty measure considers the deprivation experiences of poor people (e.g. poor health, inadequate education, insufficient living standards, income deficiency, disempowerment, and poor quality of work) and how they interrelate. Hence, this approach provides an accurate representation of multiple deprivations that different people suffer from.

Given the dimensionality and complexity of the various dimensions involved in identifying the urban poor, this study proposes a relative poverty approach in determining the poor. Urban multidimensional poverty involves several dimensions; in Malaysia, this involves education, living standard, monetary, and health dimesions (Lazim and Osman, 2009). As per the definition of urban poor, the related issue touches on how to classify the poor in urban areas so that they could also receive the welfare benefits and not miss out. This study sees Malaysia as a unique case where the urban poverty classification can be drawn into three classes: i) the needy – one who has neither material possessions nor means of livelihood; one who suffers, and has no means to sustain his or her daily needs, ii) the poor – one who has insufficient means of livelihood to meet his or her basic needs, and iii) the non-poor. The classification of multidimensional urban poverty in Malaysia could play a role in the setting up of policies in regard to the redistribution of assets and opportunities and provision of income support. Income support should be used for households that are unable to earn a living due to physical or mental disabilities.

The multidimensional poverty measures could reveal the different range of poverty that the poor are experiencing. The Alkire-Foster method measures on multidimensional poverty based on the Foster-Greer-Thorbecke poverty measures. The Alkire Foster method is a way of measuring multidimensional poverty (OPHI,

2014). This method includes on counting the multiple types of deprivation of the particular household as well as the lack of education and poor health or living standards (Alkire and Foster, 2007). The poor are identify through these deprivation profiles, which is to be used in creating the multidimensional index of poverty (MPI).
These deprivation profiles are analysed to identify the poor, and then used to construct a multidimensional index of poverty (MPI). The Alkire Foster approach is a flexible approach, which can be adapted to cater variety of deprived situations by selecting different dimensions (e.g. living standards), indicators of poverty (e.g. does the household own or rent a house), and poverty cut offs (e.g. the household that rents a house is considered to be in poverty).

There are vast number of studies that are focusing on welfare investigation particularly via an econometrics approach. Some of the methods include the partial equilibrium model (BuShehri and Wohlgenant, 2012), the multivariate ordinary least squares model (Fang, 2011), the bootstrap methodology (Jeong *et al*., 2003), the cost–benefit analysis and life satisfaction approach (Welsch, 2007), and the behavioural micro simulation modelling method (Creedy *et al*., 2011). However recently, the application of Artificial Intelligence methods has generated waves in the economic welfare field, fusing both fields into unique studies. The Adaptive Network-based Fuzzy Inference (ANFIS) method is an artificial neural network based on the Takagi-Sugeno fuzzy inference system. This method integrates both neural networks and fuzzy logic principles and thus makes the most of both techniques. The ANFIS is an inference system, which corresponds to a set of fuzzy if-then rules, enabling learning capability to approximate nonlinear functions (Abraham, 2005). ANFIS has been widely used in various economic areas, namely e-commerce (Chan *et al*., 2012), stock market and trading (Alizadeh et al., 2012; Tan *et al*., 2011; Atsalakis and Valavanis, 2009) as well as macroeconomics (Keles *et al*., 2008).

The motivation and challenges of the urban poor classification are discussed in the following sections. Next, this chapter discussed on the current methods in poverty measurement. This is followed by addressing the problems in this study. Consequently, goals and objectives of this study are presented. This is followed by the scope of this study and finally an overview of the organisation of this thesis is given.

1.2 Challenges in Urban Poverty Classification

Since the 1970s, poverty in Malaysia has been measured using an absolute measure, which includes the money metric measure, and is based on the headcounts and basic needs approach (Atkinson, 2016). In other words, poverty is a result of an inadequacy of income or consumption (Dollar *et al*., 2014; Kraay and McKenzie, 2014). Inadequacy of such a variable could be accounted for in explaining poverty; however, it is not exactly correct to measure income in terms of household. The current Poverty Line Income (PLI) approach used in Malaysia only focuses on measuring the minimum standard of living for food and non-food items. A household is considered poor if it falls below the poverty line, without taking into consideration overall household preferences. Thus, the first challenge of this study is to solve the dichotomy of the urban poor and non-poor classes, which has resulted in consumption bias and less focus on human capability and potential. Hence, a solid approach of classifying the urban poor needs to be developed to overcome this challenge.

The migration of low-income groups from rural to urban areas has resulted in the emergence of the urban poor. Low-level education, large family size, influx of foreign workers, and an increase in unemployment rate are among the factors that cause urban poverty. According to the Malaysian Economic Planning Report 2012, the income poverty line for urban areas is RM860. However, the cost of living tends to be higher in urban areas, forcing urbanites to have a higher income in order to have better access to basic amenities, health care, and education. Many urban households suffer from conditions associated with poverty even though they earn incomes that are above the poverty line. Hence, this triggers the second challenge in this study, which is the misfit urban poor classification, which has resulted in inaccurate welfare allotment by the government (Alkire and Seth, 2009).

In view of urban poverty classification, the third challenge is to minimise the predictive error rate for the proposed method in this study. Fundamentally, it is crucial to understand the concepts of urban poverty for the proposed method. The multiple predictive models are trained and combined to produce a more stable and robust model. Currently, there are very limited literatures that attempt on multidimensional poverty by using artificial intelligence, especially in by local researchers. Therefore, at the end of this study, the proposed method is compared with standard classification methods so that future researchers may improve upon the findings of this study.

1.3 Current Method of Urban Poverty Classification

According to Sen (1976), poverty measurement can be classified into two distinct steps: i) the identification step for defining the cut offs to distinguish the poor from the non-poor; and ii) the aggregation step that brings together the data of the poor as a summary of poverty indicators. The identification process is indeed very critical and thus poverty needs to be clearly defined. Each poverty definition describes the poor differently and results in different estimations and extents of poverty (Rasool *et al*., 2011). In order to comprehend urban poverty, the established definitions and concepts of poverty must first be understood.

(a) Monetary approach: this is the most commonly used approach by economists to explain poverty, and is based on the income/expenditure approach (Trani and Cannings, 2013). Thus, the poverty line serves as the minimum level of income deemed necessary to achieve an adequate standard of living in a given country. The most fundamental approach in the monetary approach is absolute poverty and relative poverty. Absolute poverty is based on the rigid poor/non-poor dichotomy, for which most of the literature on poverty measurement uses poverty thresholds (Jolliffe and Prydz, 2016). The concept of absolute poverty is that there is a minimum standard, which no one should ever fall under. This approach is commonly used in developing countries such as Malaysia. On the other hand, relative poverty is used to assess the general standard of living that prevails in society. This approach refers to a standard, which is defined in terms of the society and an individual's life, and therefore differs between countries and over time.

(b) Basic needs approach: fundamentally, basic needs approach is materialistic. This approach focuses on the well-being by identifying the basic consumption (e.g. clean water, shelter, and food) and the availability of those for the population. The household is considered poor if no adequate access into these commodities.

(c) Capability approach: this approach focuses on non-income items such as life expectancy, literacy, and infant mortality (Sen, 1985). Sen (1985) deliberates on the freedom to do necessary basic activities as a basic capability as to avoid poverty. The capability approach has been highly influential thus far (Dowding *et al*., 2012), and has led to the creation of a few major indices such as the Human Development Index, Gender-related Development Index, Gender Empowerment Measure, and Gender Inequality Index.

(d) Multidimensional Poverty Approach: this approach describes poverty in wider perspectives. The poor people are defined by including on deprivation in education, health, housing and employment. The multiple dimensions that contribute into poverty cannot be exclusively defined by monetary indicator. The Multidimensional Poverty Index (MPI) is an index that is designed to measure acute poverty (Alkire and Santos, 2011).

1.4 Problem Statement

The problem in classifying urban poverty is described as follows:

"Given a household data in an urban area, the challenge is to develop a multidimensional poverty measurement framework, which complements the money-metric measurement by considering overlapping deprivations to the poor. Therefore, the rigid dichotomy of the poor and non-poor, which results in insensitive poverty changes, needs to be overcome. A good poverty measure should be able to capture changes that happen to the urban poor in various sub-groups of the population, so that precise summary statistics of economic welfare can be produced, and hence overcoming the misfit urban poor problem. Finally, enhancements to the proposed approach should be able to minimise the predictive urban poverty error rate and increase the accuracy of classification results."

Based on the above challenges, some factors need to be addressed. The first factor is related to the current poverty measurement approach, which is the money-metric measure, which has led to the current use of the national poverty line. Malaysia uses the poverty line based on the absolute poverty measurement in order to monitor the country's progress in eradicating poverty. A household is considered poor if it falls below the poverty line, without taking into consideration overall household preferences. The circumstances of households vary with respect to their needs, thus the implementation of the rigid poverty line is actually irrelevant. The problem occurs when the poverty line is held constant, and even if the statistical rate of poverty remains the same, the composition of the poor population can change, with some of the poor climbing above the poverty line as others slip below it. A good poverty line should take into account other poverty preferences in reference to the poor. Consequently, the use of the poverty line cannot be used to accurately estimate the proportion of the society that is in poverty. Therefore, this study proposes a multidimensional poverty measure that considers the multifaceted conditions that the urban poor suffer from.

The second factor is related to the misfit urban poor issue, which arises as a result of the increase in unemployment, influx of low-income group from rural to urban areas, low education levels, and large family size. Urban poverty is more serious, harsh, and extreme compared to rural areas due to the higher cost of living in urban areas, hence urbanites need to have higher incomes to gain better basic amenities, health care, and child education. There are many households that do not have access to basic amenities even though their income is above the poverty line. These households suffer from conditions associated with poverty. Often, these groups are overlooked by national organisations and excluded from poverty eradication programmes. Thus, this study aims to predict multidimensional urban poverty indicators using an intelligent system. The result of this study highlights the prominent indicators that cause urban poverty in Bandar Tasik Selatan, Kuala Lumpur.

The third factor is related to improving upon the predictive error of the proposed method in this study. A larger predictive error rate is linked to the misclassification of data; hence, this study attempts to overcome this problem via a combination of predictive models. As this study combines elements from both the economic and Artificial Intelligence domain, it is essential to fully manipulate the variables from both domains in order to yield the best urban poverty analysis. At the end of this study, the aim is to produce a new urban poor predictive classification method, with appropriate deprivation indicators to generate accurate input-output results.

1.5 Goal and Objectives of Study

The goal of this study is to better classify the urban poor population, produce a flexible national poverty line, and implement the proposed multidimensional poverty measures in neighbouring developing countries.

In order to reach this goal, several objectives have to be completed:

(a) To classify the urban poor that will solve the dichotomy of poor and non-poor by using data-driven fuzzy rule-based system for multidimensional urban poverty classification.

(b) To resolve the problem of misfit urban poor by predicting the poverty indicators present in an urban area by combining Alkire Foster method with ANFIS algorithm.

(c) To integrate the enhancements in (a) and (b) with ensemble ANFIS in order to minimise predictive error rate.

1.6 Scope of the Study

This study uses household data acquired from the data collection phase. The household welfare data is used to analyse situations, which describe the characteristics of the situation, hence modelling the possible range of solution. However, acquiring information and knowledge on poverty measures for welfare distributions is an ongoing process, and information and knowledge need to be fed continuously. Hence, the more data gathered, and the more sophisticated the analysis, the more such decisions can be made with little or no human intervention. Data-driven poverty research is dependent on human domain experts that deal with the growth of multiple situations and find ways to deal with these problems and make better decisions. Accordingly, the human domain expert in this study is the Zakat Collection Centre Kuala Lumpur (PPZ MAIWP). This study also included the profile of PPZ MAIWPs' officials whom validated the proposed method.

The data collection was conducted in an urban province chosen purposively to meet a number of conditions that are of interest for vulnerability studies such as low per capita income, poor infrastructure, inequality in wealth, and development potential. The data collection was carried out in early March 2014. The targeted area was a small urban region, Bandar Tasik Selatan, situated in the centre of Kuala Lumpur, Malaysia. Furthermore, this study is done based on the urban area of Peninsular Malaysia Poverty Line Index (PLI), which is RM860 as of 2014.

1.7 Significance of the Study

Since the introduction of the New Economic Policy 1971-1990 (NEP), Malaysia has achieved outstanding progress in poverty eradication. However, many problems and challenges still exist in urban areas even though the incidence of urban poverty has shrank from 3.3 percent in 1999 to 2.5 percent in 2004. The rigid national poverty line has resulted in the urban poor, who earn just above the line, being classified as 'near poor'. This group is vulnerable and could slide into poverty at any time. A household can be income poor but multidimensionally non-poor, or income rich but multidimensionally poor. In this study, data-driven FRBS is initially proposed to solve the issue of artificial dichotomy between the poor and non-poor. Data from human experts is extracted using fuzzy logic and represented as a set of fuzzy membership functions. However, the issue of misfit urban poor still exists due to the money-metric measure used in the experiment. Therefore, the multidimensional poverty measure using the Alkire-Foster approach is used to measure poverty instead of the national PLI. This measure has been found to be rigorous and easily flexible for application in any policy, making it adaptable to different contexts. Compared to the PLI, this approach could be employed flexibly in a variety of different dimensions, indicators, deprivation cut offs, and weights. These could lead to an accurate distribution of welfare allotment by the Government. The urban poverty prediction is improved upon through combinations of predictive models. The poverty prediction results from the proposed model are compared with the standard classification model so that other researchers can improve upon this study in the near future.

In order to predict the effect of economic policies on household welfare, the number of deprivations of households needs to be well-understood. A review of previous economic welfare studies reveals that almost all of these studies have been based on a conventional economics approach. As this study proposes a fusion between the Artificial Intelligent and Alkire-Foster approaches, this study is able to predict the prominent poverty indicators among urban households to solve national welfare inequality.

1.7 Organisation of the Thesis

This thesis is structured into seven chapters. A brief description of each chapter is given below:

(a) Chapter 1 defines the challenges, problems, current methods, objectives, scope, and significance of the urban poor classification study.

(b) Chapter 2 reviews the related works for studied domain, which are the definition of poverty, poverty in Malaysia, urban poverty, poverty from multidimensional perspectives and poverty, econometrics, and Artificial Intelligence. The last section of this chapter presents the trend and directions related to this study.

(c) Chapter 3 starts off with a brief review of the proposed urban poor classification framework, followed by detailed descriptions of hardware and software requirements, data sources, testing and analysis procedures, and the performance measurement used.

(d) Chapter 4 highlights an initial study by proposing a data-driven fuzzy rule-based system for multidimensional classification.

(e) Chapter 5 briefly continues on improving upon the proposed method, by detailing the Alkire-Foster-based quantification method in measuring multidimensional poverty indicators using intelligent ANFIS.

(f) Chapter 6 fine tunes the predictive results by proposing an ensemble adaptive weighting and integration-based system for predicting urban poverty.

(g) Chapter 7 concludes this study and presents the contributions of the study as well as recommended future work.

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