A NEURO-FUZZY DECISION SUPPORT FRAMEWORK FOR TENANTS' SATISFACTION ASSESSMENT IN RESIDENTIAL PROPERTIES

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ABSTRACT: In real estate practice there is lack of precise information associated with property renting. Thus, prospective tenants and estate valuers require a great deal of judgment to measure and identify the best combination of property attributes to derive a high tenants' satisfaction level. Most tenants are often very dissatisfied after renting a property; this is caused by the fact that at the point of choosing the property, only one or two factors were considered to arrive at the decision, ignoring other factors which are also significant. This paper proposes a neuro-fuzzy framework that will assist prospective tenants and estate valuers in the determination of the degree of satisfaction that will be derived from any residential property before the choice of such property is made. The basic infrastructure, property facilities, environmental and neighbourhood factors are indicators in the neural network models. Neural network interpret the complex interactions between property attributes while the fuzzy logic component acts as a tool for modelling imprecise and vague knowledge in the domain of property renting and also provide membership functions for the neural networks. The system uses adaptive neuro-fuzzy inference based on Mamdani's inference mechanism to draw conclusions from fuzzy rules.

INTRODUCTION

Property renting is an estate management practice which deals with the acquisition of properties by prospective tenants over a period of time covered by rent [Benny, 2000]. Housing represents the second most essential human need after food and it has a profound impact on the health, welfare and productivity of individuals, Oladapo, (2006), Olujimi, (2010). For housing to produce these impacts, it must adequately satisfy the occupants of such property. The decision to buy or rent a property is often guided by the goal of finding a single optimal answer from the multitude of possibilities, Stahl et al , (2002), Saaty, (2008). Decision making analysis, in the domain of property renting, aims at realizing conflicts that occur due to fluctuating environmental and infrastructural conditions, varying property facilities and imprecise nature of property attributes. Improper final selection may cause unpleasant outcome which leads to misuse in resources, manpower as well as precious time. Hence, it is important to achieve an optimal decision in real world problems which involve multiple alternatives and criteria in qualitative and quantitative domains, Cheong et al, (2008).

Finding the right place to rent can be a rewarding experience or a frustrating and financially draining one. The decision represents an amalgam of many factors, and is only made after an assessment of the relative advantages or disadvantages of alternative properties. Hence, it is important to measure the anticipated degree of satisfaction from residential properties before the decision to rent a property from a list of alternative properties. There is no question that location remains the single most important factor when choosing a home, Fanning, (1994).

Some people prefer the suburbs while others thrive on downtown living. If one is inclined to favour the many benefits the city has to offer, then the choice of the part of the city that suits him best must be made. The rent for such properties also influences prospective tenants' decision, to rent a property, Herman and Schwab, (1995). Before location is considered the following factors may be used to determine how suitable the location; distance to and from work place or school, transportation issues, availability of basic social amenities, people living in that area, Department of Real Estate, (2003). Other factors that may be considered are; the type of property, facilities in the property, accessibility, and income level.

The quest for accuracy, transparency, reliability and consistency has resulted in the shift from traditional approaches in the real estate practices to advanced (computerized) techniques, Pagourtzi et al., (2003). Artificial Neural Network (ANN) and Fuzzy Logic have been offered as a possible solutions to many problems in real estate valuation, Pagourtzi et al., (2003), Guan et al., (2008). The appeal of neural network based methods lies in the fact that they do not depend on assumptions about the data and may rather replicate a prospective tenant's thought process, Guan and Levitan, (1996). Neural networks have the ability of interpreting the numerous and complex interactions of common attributes in a typical property, Guan et al., (2008). Byme and Smith, (1995) discusses the applicability of fuzzy logic in real estate analysis and contends that fuzzy logic has value as a tool for dealing with the risk and uncertainty in real estate analysis. Bagnoli and Smith, (1998) examines how fuzzy logic may be used in expressing the inherent imprecision in the way that people think and make decisions about the pricing of real estate.

In real estate practice there is lack of precise information associated with property renting, [Bagnoli and Smith, 1998]. Thus, prospective tenants and estate valuers require a great deal of judgment to measure and identify the best combination of property attributes to derive a high tenants' satisfaction level. Most tenants are often faced with lots of problems or very dissatisfied after renting a property; this is caused by the fact that at the point of choosing the property, they only considered one or two factors to arrive at the decision, ignoring other factors which are also significant.

In this paper, we propose a Neuro-Fuzzy framework for decision support systems that will assist prospective tenants and estate valuers in the determination of the degree of satisfaction that will be derived from any residential property before the choice of such property is made or degree of satisfaction derived from any residential property by any tenant before the decision to retain such property is made.

OVERVIEW OF NEURO-FUZZY SYSTEMS:

A Neural Network (NN) is a mathematical model or computational model based on biological neural networks. It is an emulation of biological neural system [Singh and Chauhan, 2009]. NNs are a method of artificial intelligence based upon models posed by cognitive theory in psychology as to how biological brains function [Hykin, 1995]. A brain is composed of neurons, cells that receive a stimulus and triggers a response from the neuron [Jain and Martin, 1998]. Fuzzy logic is based on the central idea that in fuzzy sets each element in the set can assume a value from 0 to 1, not just 0 or 1, as in classic set theory. Thus, qualitative characteristics and numerically scaled measures can exhibit gradations in the extent to which they belong to the relevant sets for evaluation. This degree of membership of each element is a measure of the element's belonging to the set, and thus of the precision with which it explains the phenomenon being evaluated [Bagnoli and Smith, 1998].

Fuzzy Inference Systems (FIS), which are based on fuzzy logic, often consist of IF-THEN rules that fire in parallel when the IF conditions are met [Inyang, 2006]. One of the main challenges of creating an FIS is the determination of fuzzy sets and fuzzy rules. Determination of such fuzzy sets and rules require deep domain knowledge from human experts and the fine tuning of the fuzzy rules and sets can be very time consuming. A solution to this problem is to combine the advantages of a fuzzy system with the learning capability of artificial neural networks

[Jang, 1993]. The result is a neuro-fuzzy system, which is, a fuzzy system that uses a learning algorithm derived from or inspired by neural network theory to determine its parameters by processing data samples [Akniyokun, 2002]. The neuro-fuzzy systems use adaptive neuro-fuzzy inference system (ANFIS). ANFIS has the features of the neural networks such as learning abilities, optimization abilities, and the fuzzy inference system such as human-like reasoning using IF-THEN rules and ease of incorporating human expert knowledge. The application of fuzzy logic and neural networks to real estate practices is demonstrated in Bagnoli and Smith, (1998), Pagourtzi et al., (2003), Guan et al., (2008) and Pagourtzi et al., (2003). In Guan and Levitan, (2008) a design and implementation of an adaptive neuro-fuzzy inference system-based approach to estimate prices for residential properties is presented.

DECISION SUPPORT FRAMEWORK

The conceptual model of the Neuro-fuzzy based decision support system for residential property renting is adapted from Inyang and Akinyokun, (2008) and Inyang et al., (2009). Its architecture is presented in Figure 1.

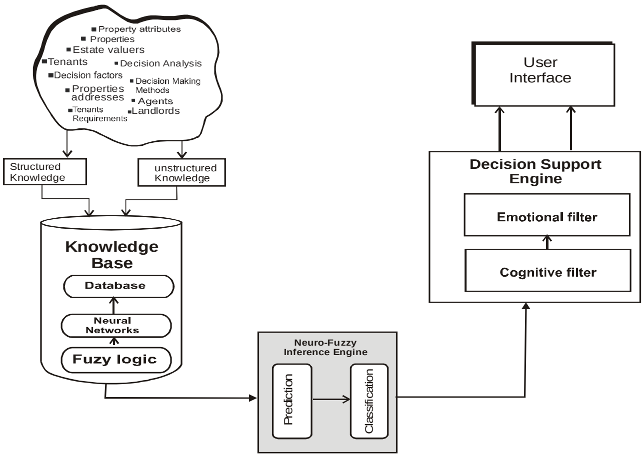

Figure 1: Architecture of the Neuro-Fuzzy Decision Support System

As shown in Figure 1, it has as components, knowledge base, Neuro-fuzzy Inference Engine, Decision Support Engine and the user interface. The knowledge base is a warehouse of the static, dynamic and temporal knowledge of the properties, properties attributes, tenants' requirements, prospective tenants, property owners etc. It has a database component that models the information of residential properties available for rent, the rental procedures, the factors considered in the choice properties. The other components are neural network and Fuzzy logic. This paper describes the design methodology of neuro-fuzzy component.

The neural network (NN) models are grouped under the following:

a. Specific attributes
b. Basic Infrastructure
c. Property facilities
d. Environment

The specific attributes represents the primary considerations of most prospective tenants when requesting for property to rent, these include location, rent, tenancy policy, property type. In the basic infrastructure NN model, the decision variables are availability of electricity, water, sewage disposal and public institutions. The basic facilities NN model consist of built in facilities in the property; its variables are toilet and bathroom, kitchen, burglary proof, space, finishing and wall fence. Accessibility, security, proximity and transportation are the indicators of environmental NN model. The block diagram of the NN network model is as shown in Figure 2 while the structure of the integrated NN model is presented in Figure 3.

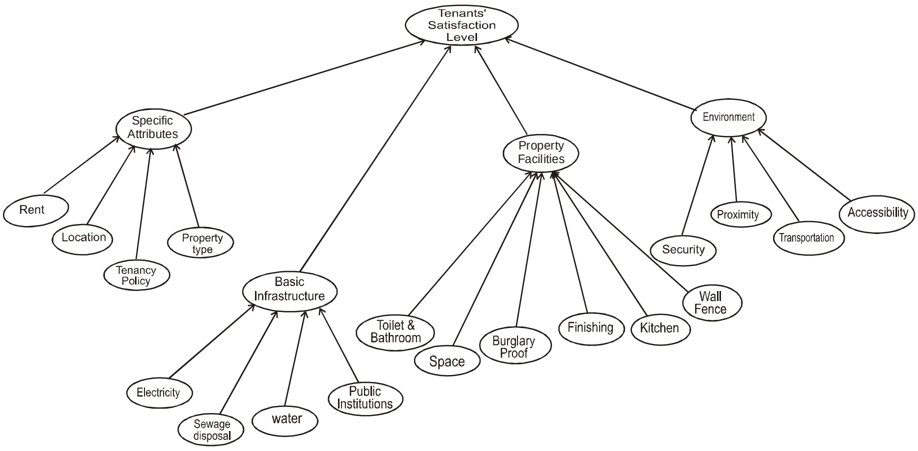

Figure 2: Block diagram of Neural Network for Property attributes

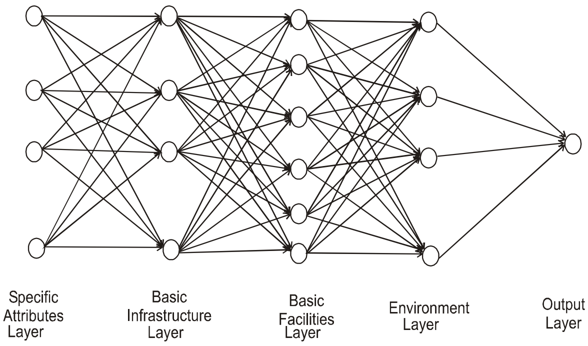

Figure 3: A 4 layered Feedforward NN model for property attributes

As shown in Figure 3, the NN model has one input layer, 3 hidden layers and 1 output layer. The specific attributes layer, basic infrastructure layer and environment layer has 4 neurons each while the basic facilities layer has 6 neurons. These neurons in each of these layers are connected to one another in order for them to provide the degree of satisfaction expected from residential properties. There are a total of 68 communication links (weights). The Neural network model is represented mathematically as follows:

$$L_j = \sum_{j=0}^{i} W_{j,k} S_k \qquad - \quad - \quad - \qquad (1)$$

$$T_j = \sigma(L_j) \qquad . \quad . \quad . \qquad (2)$$

$$S_k = \sum_{q=0}^{p} W_q T_q \qquad - \quad - \qquad (3)$$

k=1, 2, 3, 4 ; j=1,2, 3

where S_k refers to the degree of satisfaction of the k^{th} category of property attributes , w_{jk} is the weight of the link which connects k^{th} input to the j^{th} hidden node, L_j is the net input of the j^{th} hidden node, σ is the sigmoid function, w_q is weight of the link which connects q^{th} hidden node to the output node. The learning strategy is the backpropagation method.

The Fuzzy logic component provides an inference mechanism under cognitive uncertainty. It is made of fuzzification, fuzzy inference engine and defuzzification as phases. Fuzzification, involves converting the inputs from the traditional crisp universe to the fuzzy universe. For example, if V is a set of environmental attributes and its element are denoted by x, then the set *v* in V is denoted by:

$$v = \{(x, \mu_v(x)) \mid x \in V, \mu_v(x) \in [0,1]\} \qquad - \quad - \qquad (4)$$

where $\mu_v(x)$ is the membership function of x in v and specifies the degree of satisfaction that will be derived from attribute x in v in the interval of [0,1]. In this work, the fuzzy sets that describe the attributes of residential properties are {Low, Medium, High, Very High} and {poor, fair, Good, Excellent}. The set of attributes and their respective fuzzy sets are presented in Table 1.

Table 1: Property attributes and fuzzy linguistics terms

S/N	Category	Property attributes	Code	Fuzzy sets
1	Specific Attributes (SA)	Location	L	{poor, fair, good, excellent}.
2		Rent	R	{low, medium, high, very high}
3		Tenancy Policy	TP	
4		Property type	PT	{poor, fair, good, excellent}.
5	Basic Infrastructure (BI)	Electricity	EL	{poor, fair, good, excellent}.
6		Sewage disposal	SD	{poor, fair, good, excellent}.
7		Public Institutions	PI	{low, medium, high, very high}
8		Water	W	{poor, fair, good, excellent}.
9	Basic Facilities (BF)	Toilet and bathroom	TB	
10		Kitchen	KI	
11		Burglary Proof	BP	{poor, fair, good, excellent}.
12		Space	SP	
13		Finishing	FI	
14		Wall Fence	WF	
15	Environment (EN)	Accessibility	AC	{poor, fair, good, excellent}.
16		Security	SE	{low, medium, high, very high}
17		Proximity	PR	{poor, fair, good, excellent}.
18		Transportation	TR	{poor, fair, good, excellent}.

Each linguistic term is a fuzzy set and has its own membership function. The triangular membership functions are used in representing these linguistic variables. For example, the Rent for the *ith* property {RP_i} is defined by:

$$R(P_i) = \begin{cases} \text{'Very High'} & \text{if } R_r > 1.5 \\ \text{'High'} & \text{if } 1.25 < R_r \leq 1.50 \\ \text{'Medium'} & \text{if } 1.0 \leq R_r \leq 1.20 \\ \text{'Low'} & \text{if } R_r < 1.0 \\ & i = 1,2,3 \ldots n \end{cases} \quad - \quad - \quad (4)$$

where

$$R_r = \frac{AC_i}{BC_i}$$

Where BC_i is he budgeted rent of the ith property, AC_i is the Actual Rent of the ith property and n is the number of properties a prospective tent should choose from.

Pieces of knowledge are represented as production rules. The specific attribute, basic Infrastructure and environment categories, each has 16 rules, the basic facilities category has 32 rules giving a total of 80 rules in the rule base.

Examples of the rules are as follows:
IF L is *good* AND R is *medium* AND PT is *excellent* AND TP is *good* THEN SA is *Satisfactory*

IF L is *poor* AND R is *high* AND PT is *excellent* AND TP is *poor* THEN SA is *Very Dissatisfactory*

IF TB is *good* AND KI is *medium* AND BP is *excellent* AND SP is *good* AND FI is *poor* AND WF is *poor* THEN BI is *Very Satisfactory*

The graph of the membership function of the fuzzy set {*very dissatisfactory, dissatisfactory, moderately satisfactory, satisfactory, very satisfactory*} is presented in Figure 4.

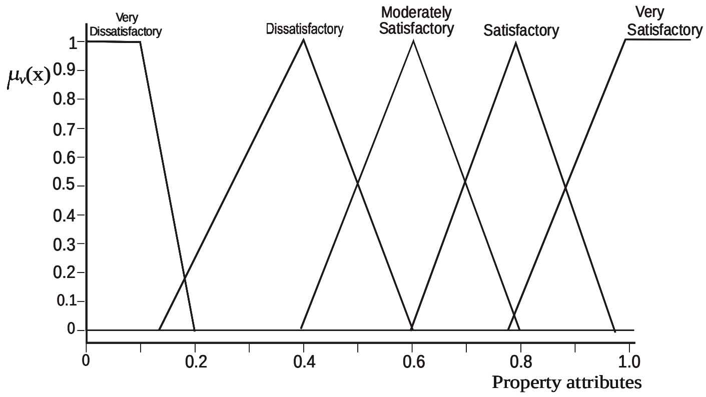

Figure 4: Graph of membership function of fuzzy sets property attributes categories

The inference system is driven by the neuro-fuzzy inference based on Mamdani's inference mechanism. The architecture is as presented in Figure 5. As shown in Figure 5, the neuro fuzzy inference is a six layered architecture of nodes. Out of the six layers, the first, second and fifth layers consist of adaptive nodes while the third, fourth and sixth layers consist of fixed nodes. The architecture implements the Mamdani's inference mechanism. It handles rules of the form:

Rule^1: *IF* (x_1 *is* A_1^1) *AND* . . . *AND* (x_m *is* A_m^1) *THEN* (y^1 *is* B^1)

Rule^n : *IF* (x_1 *is* A_1^n) *AND* . . . *AND* (x_m *is* A_m^n) *THEN* (y^n *is* B^n)

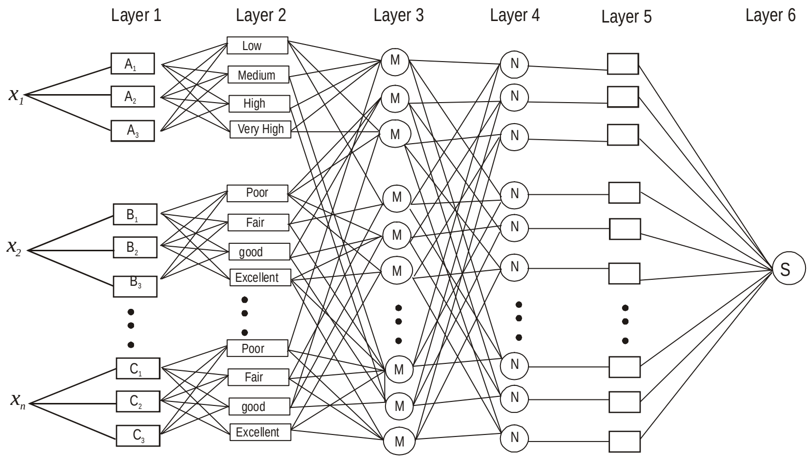

Figure 5: Adaptive neuro-fuzzy inference system for Tenant's Satisfaction measurement

where x_i are inputs, A_i are fuzzy sets of *ith* inputs variables and B_i are fuzzy sets of the outputs variables within the fuzzy region specified by the rule. As shown in Figure 5, there are n inputs to the system; the rule may therefore assume the form:

IF (x_1 *is* A_1) *AND* (x_2 *is* B_1) *AND… AND* (x_n *is* C_n) *THEN* (*S is* O_1)

In this work n = 4 , where n represents the number of property attributes group.
An example of such rule is:
IF (*SA* is *satisfactory*) AND (*EN is very satisfactory*) AND (*BF is dissatisfactory*) AND (*BI is Very satisfactory*) THEN Tenants Satisfaction is *High*

Layer 1 is the fuzzification layer. They represent inputs to the system which may be specific attributes (location, rent, tenancy policy and property type), Environmental attributes, basic facilities attributes etc. The outputs of this layer are the fuzzy membership grade of the inputs which are represented in layer 2. They represent the degree to which a given input satisfies the linguistic label associated with it. This is given by: $O^1 = \mu_{A_i}(x)$, $i=1,2,3,4$

where $\mu_{A_i}(x)$ adopts the triangular membership function and is given as

$$\mu_{A_i}(x) = \frac{x-b}{a-b} \quad - \quad - \quad - \quad (5)$$

where a and b are the parameters of the membership function governing the triangular shaped functions accordingly such that $b \leq x \leq a$

Layer 3 consists of the rule nodes, labelled M, indicating that they function as simple multipliers to compute the rule antecedent part. Each node computes the firing level of the associated rule. The output of the i^th^ neuron is

$$\alpha_i = \mu_{A_i}(x) * \mu_{B_i}(x) * \mu_{C_i}(x) = \mu_{A_i}(x) \wedge \mu_{B_i}(x) \wedge \mu_{C_i}(x) \quad - \quad - \quad (6)$$

$$\alpha_i = \text{Min}\{\mu_{A_i}(x),\ \mu_{B_i}(x),\ \mu_{C_i}(x)\}$$

Layer 4 normalizes the firing level of each rule by dividing each firing level by the sum of all the firing level of all the rules. For rule 1 the normalized firing level is given as:

$$\beta_1 = \frac{\alpha_1}{\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4} \quad . \quad . \quad . \quad (7)$$

For the i^{th} rule, the normalized version is given as :

$$\beta_i = \frac{\alpha_i}{\sum_1^n \alpha_i} \quad . \quad . \quad . \quad (8)$$

The product of each rule's normalized firing level (β_i) and the rule's output is represented in layer 5. For the i^{th} node,

$$R_i = \beta_i S_i^{-1}(\alpha_i) \quad . \quad . \quad . \quad (9)$$

where i= 1,2,…18

The summation neuron is layer 6, it computes the overall system output as the sum of all incoming signals.

$$S = \beta_1 S_1^{-1}(\alpha_1) + \beta_2 S_2^{-1}(\alpha_2) + \beta_3 S_3^{-1}(\alpha_3) + \beta_4 S_4^{-1}(\alpha_4))$$

$$= \sum_{i=1}^{n} \beta_i S_i^{-1}(\alpha_i) \quad . \quad . \quad . \quad (10)$$

The output (S) of the neuro fuzzy inference systems is in crisp form and is the predicted degree of satisfaction and suitable for decision making; based on this value the tenant's satisfaction level is classified using the fuzzy set {Very Low, Low, medium, High, Very High} and defined as follows:

$$TS(S) = \begin{cases} \text{"Very Low"} & \text{if } S < 0.1 \\ \text{"Low"} & \text{if } 0.1 \leq S < 0.4 \\ \text{"Medium"} & \text{if } 0.4 \leq S < 0.6 \\ \text{"High"} & \text{if } 0.6 \leq S < 0.8 \\ \text{"Very High"} & \text{if } 0.8 \leq S \leq 1.0 \end{cases} \qquad (11)$$

Based on the result the list of properties presented to any prospective tenants can be ranked in descending order of crisp value of S. The result is passed into the decision support system where cognitive filter will pick the property with the highest rank while emotional filter may choose any property from the best three ranked properties.

CONCLUSION

The quest for accuracy, transparency, reliability and consistency has resulted in the shift from traditional approaches in the real estate practices to computerized techniques. Decision making analysis, in the domain of property renting, aims at realizing conflicts that occur due to, fluctuating environmental and infrastructural conditions, varying property facilities and imprecise nature of property attributes. This paper proposes a neuro-fuzzy framework that will assist prospective tenants and estate valuers in the determination of the degree of satisfaction that will be derived from any residential property before the choice of such property is made. The basic infrastructure, property facilities, environmental and neighbourhood factors are indicators in the neural network models. The design is flexible, user friendly and allows users to specify the relative importance of factors based on users' set of preferences, integrates these criteria into a single evaluation score and give a priority ranking of properties. The work demonstrates the application of neural network, fuzzy logic and neuro-fuzzy systems in the domain of real estate practices.

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