Applicability of Artificial Neural Network in Predicting House Rent

by

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ABSTRACT

House rent prediction has great importance in real estate development as well as in overall housing situation of a city. The various participants in the real estate market have a substantial interest in the prediction of house rent. Rent models can be an effective tool when empirical data cannot be collected either because of practical constraints of cost, time etc. or when future scenarios are being dealt with. Hedonic price (multiple regression) models have been commonly used to estimate house rent. To address the issue of application of Artificial Neural Network (ANN) in house rent prediction, this study aims to develop an artificial neural network model for house rent prediction. The study will also use the results from a hedonic price model for house rent prediction and compare the predictive power of both models.

The data set used to develop the Neural Network Model consists of a sample of 479 single family and multi-family residential properties available for rent in Rajshahi City. The neural network model built for this data set utilized fourteen independent variables. The neural network models developed in this study are the "best" models that were obtained utilizing a sequential trial and error method. The best model developed with eighty hidden neurons had the R^2 value of 0.621 for sample forecast. The study has demonstrated that neighborhood attributes are the most significant factors in determining the house rent of Rajshahi City. The percentage of area dedicated to community facilities and percentage of area dedicated to commercial use have contributed more to the predictive power of model than the other attributes. So it is seen that land use has a great impact on house rent in Rajshahi City.

The study also empirically compares the predictive power of the artificial neural network model with the hedonic price model on house rent prediction. The comparison was conducted in six stages or cases. The results indicate that the neural network model outperformed the hedonic price model in all of the cases. In this study, the ANN model consistently gave better result than the hedonic price model, although the difference between the two models was not too large. ANN model and hedonic price model both do better when they are trained and tested with the same data set but they performed poorer on out-of –sample forecast. But in both cases ANN model showed better results in comparison to hedonic price model. The study also supports the superiority of ANN model in prediction of outlier holdout sample.

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Chapter 1
INTRODUCTION

Chapter 1: Introduction

1.1 Background of the Study

The housing sector is very much associated with the economic health and wealth of a nation. A high demand for housing would trigger growth in many other economic sectors. For many households, owner-occupied housing is not only a place to live but also the single most important asset in their portfolio. Indeed, in most countries real estate is the greatest component in the private households' wealth. As a consequence, the value of their home has a major impact on households' consumption and savings opportunities. House rents are therefore of great interest to actual and potential home owners but also to real estate developers, banks, policy makers or, in short, the general public.

In Bangladesh most people know the benefit of owning a house, because buying a house is considered the most profitable investment. Most of the house owners of cities like Dhaka, Rajshahi etc. earn money by renting their houses. There is a huge demand for rented houses in urban areas of Bangladesh. House rent in urban areas of Bangladesh is rapidly increasing day by day. The growing rents are of particular problem to the lower income groups, but the issue of rental housing policy is seldom addressed by the public authorities in Bangladesh (Sharmeen, 2007).

House rent prediction has great importance in real estate development as well as in overall housing situation of a city. A reliable prediction of the house rent is important for planners, prospective homeowners, developers, investors, appraisers, tax assessors and other real estate market participants (Limsombunchai *et al.*, 2004). The various participants in the real estate market have a substantial interest in the prediction of house rent. If investors, developers or other participants wish to judge the attractiveness of individual real estate projects, an assessment of the (uncertain) prices and rents in the market segment should constitute an essential element in the decision process. Especially institutional investors, such as pension or investment funds require reliable information regarding house rent and prices. With regard to questions of asset allocation (i.e. the distribution of a given budget among the main investment sectors, such as stocks, bonds and real estate), information about returns and risk profiles of real estate and their correlation with other types of investment is of central importance. Finally, Public authorities formulate different policy measures, assess holding tax, regulate rents, grant rental allowances, allow tax deduction for mortgage payment, or subsidize the construction of public housing to make housing affordable to all groups of the society on the basis of rent. Rent models can be an effective tool when empirical data cannot be collected either because of practical constraints of cost, time etc. or when future scenarios are being dealt with.

Hedonic price (multiple regression) models have been commonly used to estimate house rent and property values. But this method has received criticism from the academic and practitioner communities. Multiple regression has often produced serious problems for real estate appraisal that primarily result from multicollinearity issues in the independent variables and from the inclusion of outlier properties in the sample (Worzala *et al.*, 1995). Moreover, nonlinearity within the data may make multiple regression an inadequate model for market that requires precise and fast responses (Brunson et al. 1994; Do and Grudnitski, 1992). Rossini (1997) points out the disadvantage of hedonic price model in terms of small data sets. Multiple regression has been widely expounded by those who belong to the quantitative school though early use of regression analysis was criticized due to its "black box" approach, in which there was limited discussion of the underlying rationale for the selection of variables and interpretation of outcomes (McGreal et al. 1997).

Kang and Reichert (1991) recommended that when a homogeneous property sample exists, hedonic pricing models may be used effectively a priori to determine the adjustment factors that should be used for each independent variable in a manual sales comparison process. Gilson (1992) advocates a more conservative use of hedonic pricing models. Gilson concludes that the regression-derived adjustments should support rather than replace any manually-determined sales comparison price adjustments or even final estimated market values. In fact, most of the related research recommends a critical application of hedonic price techniques. Do and

Grudnitski (1992) claims that although multiple regression alleviates some of the shortcomings of traditional appraisals, often its assessments result in significant appraisal errors. Further, issues such as model specification procedures, multicollinearity, independent variable interactions, heteroscedasticity, non-linearity and outlier data points can seriously hinder the performance of hedonic pricing models in real estate valuations (Lenk et al. 1996). A few studies have investigated the usefulness of hedonic models to determine the value of outlier properties. Borst (1992), Birch et al. (1991) and Isakson (1986) conclude that these models are ineffective estimators of outlier values. They recommend separate, manual analysis for properties that are dissimilar from the prediction model's training data set.

Recently, neural network models, inspired by the neural architecture of the brain, have been developed and successfully applied across a variety disciplines including psychology, genetics, linguistics, engineering, computer science and economics. Neural networks seem particularly well suited to find accurate solutions in an environment such as residential appraisal, characterized by complex, noisy, irrelevant or partial information or imprecisely defined functional models (Do and Grudnitiski, 1992). Artificial neural networks have been offered as a solution to address the criticisms associated with hedonic model approaches. The use of these models is similar to the process utilized in building hedonic pricing models: an artificial neural network model must first be trained from a set of data and the model is then utilized to estimate the prices of new properties from the same market. Supporters of artificial neural networks purport that these models eliminate the non-linearity and outlier problems inherent to the hedonic pricing techniques (Brunson et al. 1994; Do and Grudnitiski, 1992; Evans et al. 1992; Tay and Ho, 1991). However, there are limited studies in this area using an artificial neural network technique (Limsombunchai *et al.*, 2004). This study will investigate the applicability of Artificial Neural Network (ANN) in house rent prediction. The primary goal of this research is to develop an artificial neural network model for house rent prediction. The study will also use the results from a hedonic price model for house rent prediction and compare the predictive power of both models.

1.2 Objectives of the Study

The specific objectives of the study are given below:

- To develop an Artificial Neural Network (ANN) model for house rent prediction.
- To assess the relative influence of different attributes on house rent using artificial neural network
- To compare the predictive power of the artificial neural network model with that of a hedonic price model for house rent prediction.

1.3 Scope of the Study

This study investigated several aspects of the use of neural networks as a tool for predicting house rent. In particular, using a database of previous study, the study evaluated the ability of a neural network model to predict the rent of residential properties in a test sample within an acceptable range.

The study compared the importance of different attributes in house rent prediction by using the relative importance values of inputs estimated by the neural network models. Hence the importance of inputs estimated by the neural network model for the particular residential properties are only true for this specific study, not for other residential properties of different areas. Some cases were constructed in this study to test and compare the predictive power of several different neural network models and hedonic price models.

1.4 Limitation of the Study

To compare the ANN model with hedonic price model this study roughly followed the methodology used by Worzala *et al.* (1995). Longitudinal (time-dependent) data analysis is required for more reliable evidence of applicability of neural network in house rent prediction. But this longitudinal method can not be applied in this study due to unavailability of time series data of house rent. Finally, the house rent could be affected by some other factors (such as quality of the environment, traffic noise and volume, interest rate, employment, income level and other socio-economic characteristics of area) which are not included in the development of the ANN model.

1.5 Organization of the Study

This dissertation comprises of seven chapters. The first chapter presents an introduction with the backgrouud and methodology of the study. The second chapter gives an idea of artificial neural network model and its application to the valuation of residential property. The third chapter provides an overview of the selected study area. The fourth chapter consists of study design methodology from selection of variables to determination of the ANN model with an overall description of the variables used in this study. The fifth chapter comprises of the results of developed ANN model and relative contribution of different attributes in house rent prediction. The sixth chapter provides a comparative analysis between ANN model and hedonic price model in predicting house rent. Finally, chapter seven summarizes the important findings of this study and gives some recommendations regarding the application of the model.

Chapter 2
LITERATURE REVIEW

Chapter 2: Literature Review

2.1 Introduction

Hedonic price model has been commonly used to estimate house rent and property value. Recently artificial neural network has been used as an alternative model of hedonic price model approaches. So it is necessary to understand the concept of artificial neural network before applying this model in house rent prediction. The basic notions of the study are presented in this chapter based on an extensive literature review.

2.2 Artificial Neural Network Model

2.2.1. Neural network systems

A neural network system is an artificial intelligence model that replicates the human brain's learning process. The brain's neurons are the basic processing units that receive signals from and send signals to many nervous system channels throughout the human body. When the body senses an input experience, the nervous system carries many messages describing the input to the brain. The brain's neurons interpret the information from these input signals by passing the information through synapses that combine and transform the data. A response is ultimately created when the information processing is complete. Through repetition of stimuli and feedback of responses, the brain learns the optimal processing and response to the stimuli. The brain's actual learning path is still somewhat of a chemical mystery; what is known is that learning does occur and reoccur through the repetition of the input stimuli and the output response(s).

Artificial neural networks were developed utilizing this "black box" concept. Just as a human brain learns with repetition of similar stimuli, a neural network trains itself with historical pairs of input and output data. Neural networks usually operate without an a priori theory that guides or restricts the relationship between the inputs and the outputs. The ultimate accuracy of the predicted output response, rather than the description of the specific path(s) or relationship(s) between the inputs and the output response, is the goal of the model.

In an artificial neural network, nodes are used to represent the brain's neurons and these nodes are connected to each other in layers of processing. Figure 1 illustrates the three types of layers of nodes: the input layer, the hidden layer or layers (representing the synapses) and the output layer. The input layer contains data from the measures of explanatory or independent variables. This data is passed through the nodes of the hidden layer(s) to the output layer, which represents the dependent variable(s).

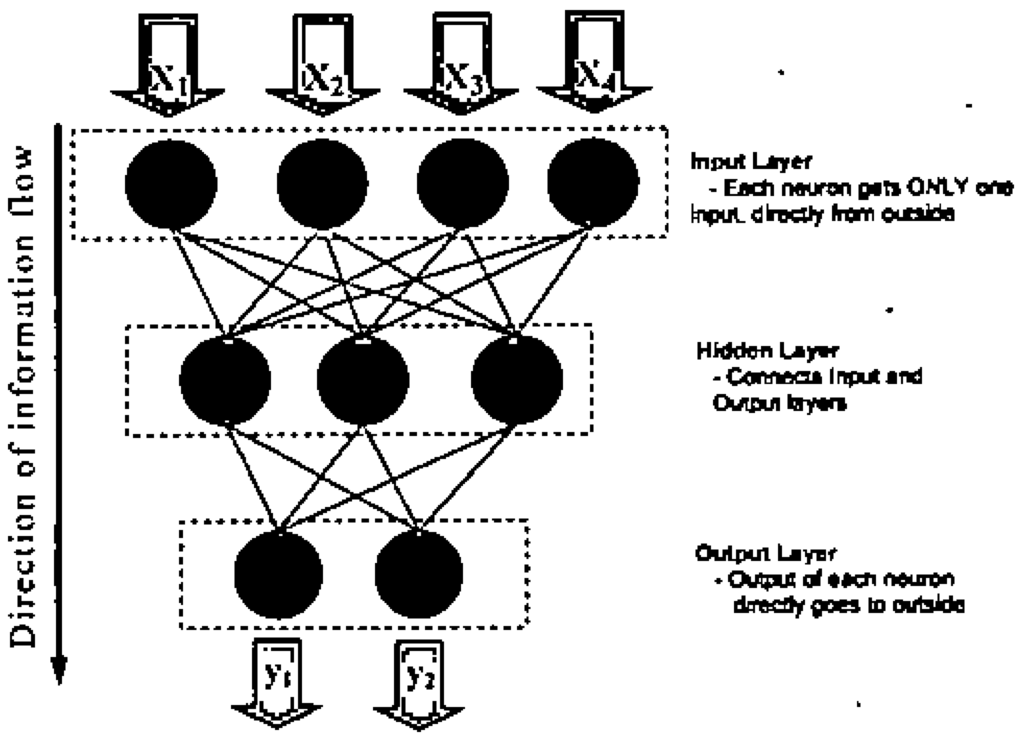


Figure 2.1: Neural Network Structure

The hidden layer(s) contain two processes: the weighted summation functions; and the transformation functions. Both of these functions relate the values from the input data (e.g. the property attributes) to the output measures (e.g. the sales price). The weighted summation function typically used in a feed-forward/back propagation neural network model is:

$$Y_j = \sum_{j}^{n} X_i W_{ij}$$

Where X_i is the input values and W_{ij} is the weights assigned to the input values for each of the j hidden layer nodes. A transformation function then relates the summation value(s) of the hidden layer(s) to the output variable value(s) or Y_j. This transformation function can be of many different forms: linear functions, linear threshold functions, step linear functions, sigmoid functions or Gaussian functions. Most software products utilize a regular sigmoid transformation function such as:

$$Y_T = \frac{1}{1+e^{-y}}$$

This function is preferred due to its non-linearity, continuity, monotonicity, and continual differentiability properties (Borst, 1992; Trippi and Turban, 1993).

In most research, the initial neural network model is created utilizing a training set of input and output data. The most common form of neural network systems are termed "feed-forward" networks and begin with a default of randomly determined weights for each of the nodes in the hidden layer. The software feeds the input measures forward through the hidden layers. At each hidden layer, the information is transformed by a nonlinear transformation function to produce an output measure. The model then compares the model's output to the historical or actual output for discrepancy. If a discrepancy exists, the model works backwards from the output layer back through the hidden layer nodes, adjusting the weights so as to reduce the prediction error. This method of error correction is usually referred to as back-propagation. With each ordered pair of input measures and output responses from the training data set, the neural network repeats these steps until the overall prediction error is minimized. In practice, the neural network stops training when it either reaches the default level of error or the researcher's pre designated maximum level of allowable error.

A trained neural network model can be tested for accuracy by letting it predict responses from new input measures. The neural network model's predictions can then be compared with the actual output for accuracy. The objective of the neural network is to find the set of weights for the explanatory variables that minimize the error between the neural network output and the actual data (Allen and Zumwalt, 1994). This similarity between neural networks and traditional statistics provides the opportunity for real estate appraisers to consider the use of this technology as a possible alternative to more common statistical techniques, such as multiple regressions (Brunson et al., 1994).

Disadvantages associated with neural networks are the speed of the learning process, the black-box nature of the back propagation training process and interpretation of the learned outpnt. The latter two problems arise from the fact that the internal characteristics of a trained net are simply a set of numbers and therefore very difficult to relate back to the application in a meaningful fashion. In this respect rule induction, the automated process by which a decision tree is built is more explicit with rules identified to distinguish between different records within the data set (McGreal et al., 1997).

2.2.2 Application of neural networks to the valuation of residential property

From the early 1990s it was started to apply neural network technology to the valuation of residential property. Frequently these studies are in the form of comparative analysis, with researchers contrasting the findings and perceived efficiency of neural network models with more tried and tested statistical methods. Given the potential difficulties associated with regression modelling, namely functional form and non-linearity of variables (Adair *et al.*, 1996), neural networks have found a measure of intuitive appeal (Borst, 1992). Indeed, Do and Grudnitski (1992) concluded that a neural network model performs better than a multiple regression model for estimating the value of U.S. residential property. In related research, Do and Grudnitski (1993) utilized neural networks to investigate the relationship of structure age to property price. Their results demonstrated that structure age has a non-linear effect on price rather than the strict negative monotonic relationship that is typically modelled with the hedonic pricing technique. The authors contend that this result supports the use of a non-linear technique, such as artificial neural networks, to appraise real estate.

Tay and Ho (1991) in a comparable study in Singapore, based on a larger sample (833 properties in the training sample and 222 in the test sample) of data from the apartment sector, reached similar conclusions with a mean absolute error of 3.9 per cent for the neural network model relative to 7.5 per cent for the regression model. In arguing the case for the use of neural networks in the mass appraisal of residential property, Tay and Ho are of the opinion that the network can learn valuation patterns for "true" open market sales in the presence of some "noise" (i.e. non-bona fide sales) as a way of establishing a robust estimator.

Borst (1992) utilized artificial neural networks and tested the predictive effects of data transformation, the exclusion of outliers, and the use of several output layer nodes to represent different price ranges or markets. Borst's neural network model boasted low mean absolute errors (8.7 per cent to 12.4 per cent) and he concluded that this new technique deserves strong consideration in the field of mass valuation.

Within the UK, Evans *et al.* (1992) tested the predictive accuracy of neural networks for estimating residential property prices and although based upon a small data set of 34 properties sold over a six month period, the results showed a reasonable level of accuracy with a mean absolute error of 13.48 per cent. Removal of outliers from both the training and test data resulted in a reduction in the mean absolute error to 5.03 per cent, conferring with Borst's inference that when outliers are removed from data sets, neural network models work well to value property. However, in drawing conclusions, they consider that neural networks are best regarded as a tool to assist, rather than as a system which could replace the valuer, pointing out that accuracy is extremely dependent on the careful choice of data for the training set.

McCluskey (1996) applied neural network technology on a sample of 416 residential properties sold from August 1992 to August 1994 in Northern Ireland, with 375 properties used to train the network. Initial results produced a mean absolute percentage error of 15.7 per cent and a predictive accuracy of 72 per cent, though removal of outliers improved the analysis (mean absolute percentage error of 7.75 per cent and a predictive accuracy of 93.6 per cent) leading McCluskey to conclude that neural networks excel in determining direct and indirect patterns of value related to property attributes. McCluskey's work, based upon data covering a two year period, encompasses an appreciably longer time-span than employed in other comparable studies. Although including a time-based variable, reverse date of sale, McCluskey attaches little significance to this variable apart from reference to the model's ability to learn the underlying pattern of values across property types reflecting both time and locational differences.

Worzala *et al.* (1995) adopt a contrary position and cast some doubt upon the role of neural networks *vis-à-vis* traditional regression analysis models, suggesting that caution is needed when working with neural networks. In undertaking analysis at varying levels of investigation and utilizing different neural network shells, the error magnitude for individual properties was found in some cases to be very significant (up to 70 per cent) and clearly not acceptable for a professional appraisal. Furthermore, the analysis showed that even when using the same data, results from models prepared by different neural network software packages could be inconsistent and do not always outperform regression models. Worzala *et al.* (1995) identify the need for further research regarding the application of neural network software before a final judgment is made concerning suitability to property appraisal/valuation. Indeed, follow-on work from Lenk *et al.* (1997) infers that substantial value estimation errors are possible, with at least one in six properties having value estimates in excess of 15 per cent of the actual price. Furthermore, by illustrating that 70 per cent of the outlier property predictions had estimation errors in excess of 15 per cent, Lenk *et al.* (1997) strongly maintain that outliers should be removed from the data. This position contrasts sharply with that advocated by Tay and Ho.

McGreal *et al.* (1997) evaluated the ability of a neural network model to predict the value of properties in a test sample within a range acceptable for valuation purposes by using a database of market sales. The best models showed that only 80 percent of properties achieve a predicted value within 15 percent of sale price which would be beyond the bounds of acceptability by the valuation profession. Various researchers have commented upon the black box nature of neural networks and the possibility of achieving opposite results with different models or model settings (Worzala *et al.*, 1995). McGreal *et al.* (1997) reinforced this argument with varying outcomes between rule and net based models as the valuation threshold is altered.

2.3 Hedonic Price Model Approach in House Rent Prediction

The hedonic price model, derived mostly from Lancaster's (1966) consumer theory and Rosen's (1974) model, posits that a good possesses a myriad of attributes that combine to form bundles of utility-affecting attributes that the consumer values. In Rosen's approach, residential properties are characterized as a set of complex heterogeneous goods. At the same time, each property or good consists of an inseparable bundle of homogeneous attributes that differ in values and characteristics. The underlying theory for the market of heterogeneous good states that the price of the good is a function of the levels or value of each attribute in the bundle. In the housing market, these attributes are usually structural and site characteristics of a property.

Hedonic price theory assumes that a commodity such as a house can be viewed as an aggregation of individual components or attributes. Consumers are assumed to purchase goods embodying bundles of attributes that maximize their underlying utility functions. Rosen (1974) describes the process in which prices reveal quality variations as relying on producers who "tailor their goods to embody final characteristics described by customers and receive returns for serving economic functions as mediaries". Hedonic price theory originates from Lancaster's (1966) proposal that goods are inputs in the activity of consumption, with an end product of a set of characteristics.

Bundles of characteristics rather than bundles of goods are ranked according to their utility bearing abilities. Attributes (for example, characteristics of a house such as number of bedrooms, number of bathrooms, number of fireplaces, parking facilities, living area and lot size) are implicitly embodied in goods and their observed market prices. The amount or presence of attributes with the commodities defines a set of implicit or "hedonic" prices (Lancaster, 1966). The marginal implicit values of the attributes are obtained by differentiating the hedonic price function with respect to each attribute (McMillan *et al.*, 1980). The advantage of the hedonic methods is that they control for the characteristics of properties, thus allowing the analyst to distinguish the impact of changing sample composition from actual property appreciation.

While the hedonic technique is an acceptable method for accommodating attribute differences in a house price determination model, it is generally unrealistic to deal with the housing market in any geographical area as a single unit. Therefore, it seems more reasonable to introduce geographical information or location factor into a model that allows shifts in the house price level. Frew and Wilson (2000) employ the hedonic price model to examine the relationship between location and property value, in Portland, Oregon, and the authors found that there was a significant relationship between location and property value. Fletcher *et al.* (2000) examine whether it is more appropriate to use aggregate or disaggregate data in forecasting house price using the hedonic analysis. It is found that the hedonic price coefficients of some attributes are not stable between locations, property types and age.

However, it is argued that this can be effectively modeled with an aggregate method. The hedonic price model has also been used to estimate individual external effects (e.g. environmental attribute) on house prices (Limsombunchai *et al.*, 2004).

2.4 Artificial Neural Network Vs Hedonic Price Model in House Rent Prediction

Even though the hedonic price model has been widely recognized, issues such as model specification procedures, multicollinearity, independent variable interactions, heteroscedasticity, non-linearity and outlier data points can seriously hinder the performance of hedonic price model in real estate valuations. The artificial neural network model has been offered as a possible solution to many of these problems, especially when the data patterns show non-linearity (Lenk *et al*, 1997; Owen and Howard, 1998). Tay (1991) using a large sample of data from the apartment sector in Singapore, found that a neural network model performs better than a multiple regression model for estimating value. Do and Grudnitski (1992), Borst (1992) and McCluskey (1996) gave same results in their studies.

Do and Grudnitski (1992) reported significant superior predictive performance by their artificial neural network model when estimating 105 residential property values. Their neural network model results contained twice the number of predicted values within 5 per cent of actual sales price as their hedonic model (40 per cent vs. 20 per cent). Furthermore, the mean absolute error from their neural network model was significantly lower than the mean absolute error from the hedonic model (6.9 per cent vs. 11.3 per cent).

Artificial neural networks have not always produced superior real estate price estimations over hedonic models. Worzala *et al.* (1995) directly challenged the findings of both Do and Grudnitski (1992) and Borst (1992). These researchers were unable to replicate the superiority of the artificial neural network model over the more traditional hedonic model when they applied the methodology of the prior studies to a new data set, even after manipulating the number of hidden layers, the number of nodes within the hidden layer(s), and the hidden layer error threshold levels of their neural network model. In each case tested, their hedonic pricing model either did better than or performed similarly to their best artificial neural network model.

Limsombunchai *et al.* (2004) compared the predictive power of the hedonic price model with an artificial neural network model on house price prediction by using 200 houses information in Christchurch, New Zealand. The results from hedonic price models of this study support the previous findings. Even, if the R^2 of hedonic price models are high (higher than 75%) in sample forecast, the hedonic price models do not outperform neural network models. Moreover, the hedonic price models show poor results on out-of-sample forecast, especially when comparing with the neural network models. The empirical evidence presented in this study supported the potential of neural network on house price prediction. The artificial neural network model can overcome some of the problems related to the data patterns and underlying assumption of the hedonic model (Limsombunchai *et al.*, 2004).

James (1996) points out the advantages of neural networks in terms of small data sets. Neural networks would seem to be a better tool for smaller data sets while regression is clearly superior for larger data sets. Regression is statistically poor with small data sets, a problem not encountered by neural networks (Rossini, 1997). Rossini (1997) supported the superiority of neural networks for small data sets based upon the time required to produce the model. Regression results can be calculated very quickly regardless of the size of the problem while the time needed to produce neural networks seems to increase exponentially with the size of the data set.

Motivated by these conflicting conclusions concerning the usefulness of neural networks to predict value, the premise for this study was to provide further evidence concerning the Do and Grudnitski (1992) and Borst (1992) conclusions that neural network models significantly outperform hedonic price models in house rent prediction.

2.5 Summary

The literature shows that there was mixed success with the ANN method, probably due to different variable inputs and market conditions. While Borst (1992) and McCluskey (1996) stated that the predictive abilities of ANN were well established through investigative studies, James (1996) feels that more work must be done on "real world data sets in order to validate the methods for use in appraisal". Since no such study was performed based on Bangladeshi data, this study seeks to apply the ANN model to Bangladeshi data. The results of this study would go some way to establishing the usefulness of this method to Bangladeshi market condition. On the basis of the concepts and techniques illustrated in literature review the following chapter presents analytical methodology of the study.

Chapter 3

METHODOLOGY AND STUDY DESIGN

Chapter 3: Methodology and Study Design

3.1 Introduction

To achieve the objectives of the study it is necessary to develop a methodology for the study. The methodology used for developing the neural network model for house rent prediction is described in this chapter. The collection procedure of data, selection criteria of different variables and characteristics of different data are portrayed in the following sections.

3.2 Methodology of the Study

The preliminary step of the study starts with extensive literature survey and review to develop a clear understating of the concepts of artificial neural network and its application for house rent prediction. It also provides familiarity with concepts of hedonic price models. In this stage the objectives of the study have been formulated. Three objectives have been identified for this study. Then, the dependent and independent variables are identified based on the variables used in an already developed hedonic price model. All the data used in this study have been collected from secondary source. Different statistical software is used to prepare inputs of artificial neural network (ANN) model development. For the development of ANN model, a back-propagation neural network software package is used. Finally different statistical analyses are performed using different statistical software for making comparison between ANN model and hedonic price model. Figure 1.1 provides with an overview of the methodological framework discussed above.

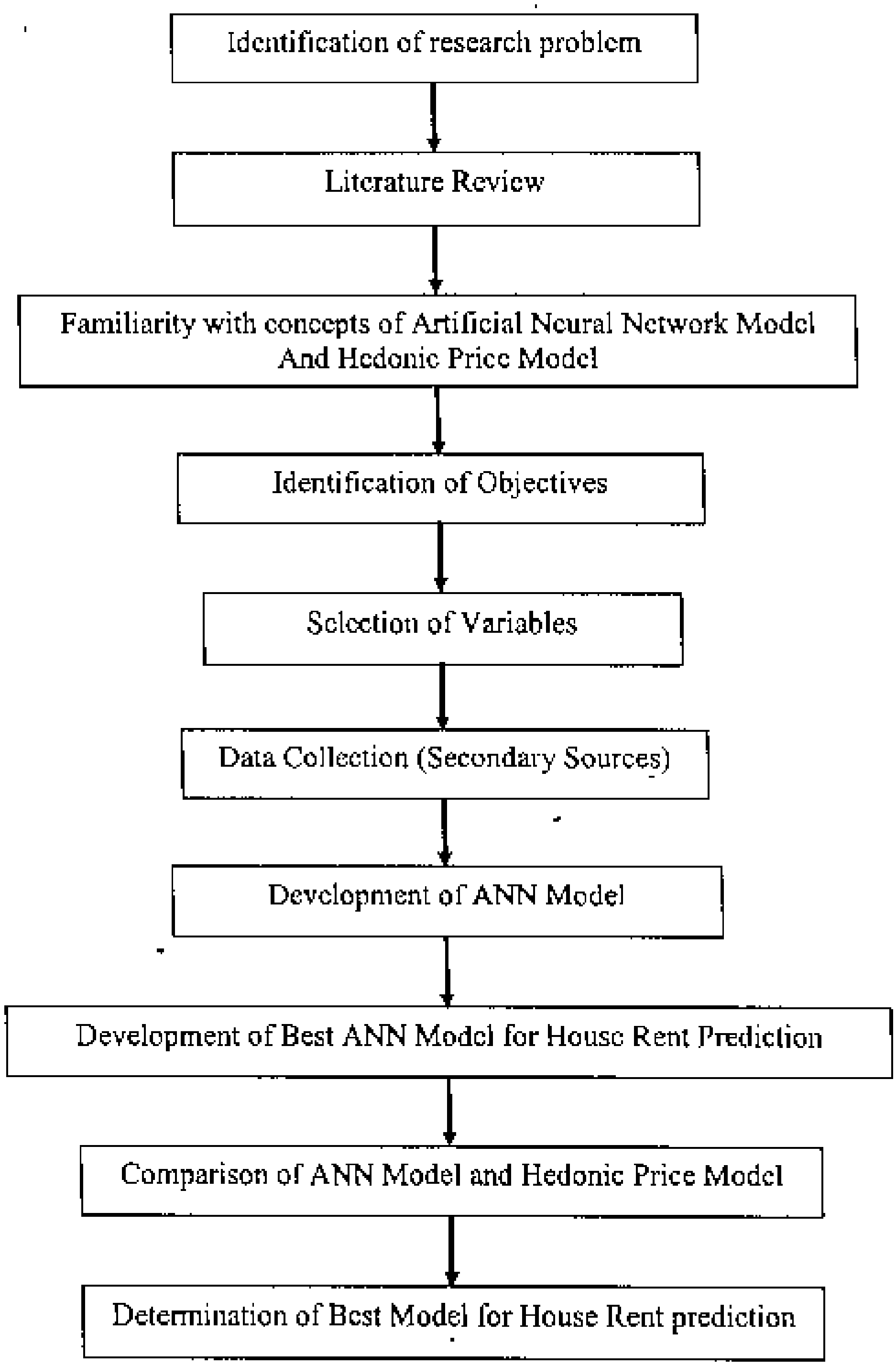


Figure 3.1: Methodological Framework of the Study

3.3 Study Design

3.3.1 Selection of variables and study area

One of the main objectives of this study is to compare the predictive of power of artificial neural network (ANN) model with the hedonic price model for house rent predication. To do this an already developed hedonic price model for house rent prediction of Rajshahi City (Habib, 2004) has been used. To ensure the similarity of the variables of the hedonic price model utilized by Habib (2004), the ANN models in this study have been built using same independent variables and same study area. In hedonic price models three types of attributes are used, namely structural attributes, neighborhood attributes and transportation attributes. In the aforementioned model, these three attributes include fourteen independent variables which are discussed in the following sections. Rajshahi City Corporation area has been selected as the study area of this study to keep the similarity with Habib (2004).

3.3.1.1 Residential asking rental price

To develop the ANN model residential advertised rental prices (in Taka during May 2004 period) have been selected as the dependent variable. There are two major characteristics of the dependent variable used by Habib (2004). The first one is related to the use of rental price instead of selling price or land value. The second one refers to the use of the asking rental price instead of the actual or market rental price.

3.3.1.2 Structural attributes

Prices of properties are frequently related to their structural attributes. Structural attributes include usable living area (in square feet), number of bedrooms and total number of bathrooms. In addition, age of building was used as a proxy for structural quality of house. The use of this proxy variable in hedonic price model was justified on the premise that structures tend to wear out with age or become obsolete, which may reduce the potential marketability of the property (Habib, 2004).

3.3.1.3 Neighborhood attributes

Since measures of neighborhood quality and neighborhood-level externalities are expected to influence residential property rent prices, a set of demographic, land use and amenities at the neighborhood level were included in the study design of Habib (2004). Most of these variables required the use of an elaborate GIS-aided approach to assign neighborhood-level data to each residential property. The hedonic price models were specified with population density as a demographic variable which was measured by persons per acre at each ward (the lower-tier administrative unit of the city corporation investigated). Land use variables includes the percentage of urbanized area dedicated to commercial land uses, residential land uses or community facilities. The percentage of area dedicated to each specific land use at ward level was obtained from Rajshahi Master Plan Project for the year 2004. Both land use and population density data for the wards were assigned to the individual residential properties that fall inside the respective wards (Habib, 2004). As for amenity variables, only the Euclidian distance to nearest drainage network is considered in this study.

3.3.1.4 Transportation attributes

Following most other studies, Habib (2004) selected the accessibility to the central Business District (CBD) as a transportation attribute for developing the hedonic price model. The other transportation attributes include accessibility to the major roads (city arterials from the individual residential properties at Rajshahi, accessibility to the wholesale markets, shopping centers and educational institutions.

Since basic educational institutions are major concerns and necessity at the neighborhood level, only primary schools were considered for accessibility to the educational institutes. Accessibility to the wholesale markets includes three major wholesale shopping agglomerations in the Rajshahi City. Besides retail shopping and commercial markets are considered as the shopping centers. The description of variables is summarized in Table 3.1.

3.3.2 Collection of data

To ensure the similarity of data set of the hedonic price model utilized by Habib (2004), the same data set was used in this study to develop the ANN model. The study was also supported by the GIS database produced by the Rajshahi Master Plan Project.

3.3.3 Development of ANN models

To develop the ANN models a back-propagation neural network software package, *NeuroShell* (Ward Systems Group, Inc.), has been used. The study used SPSS and Microsoft Excel for statistical analysis to compare the two models.

3.4 Data

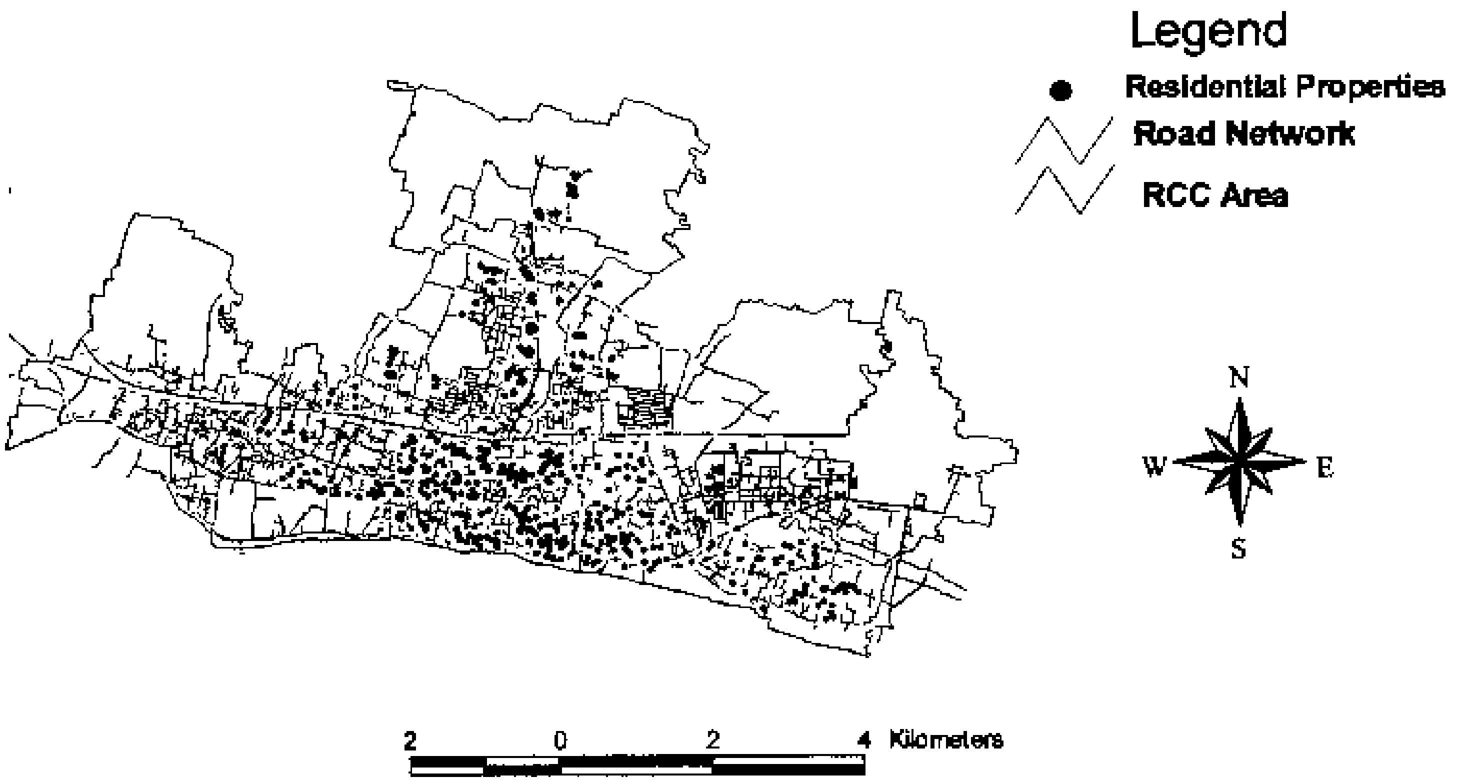
The data set of this study consists of a sample of 479 single-family and multi-family residential properties available for rent which was the final data set for the hedonic price model. In Habib (2000) study, residential properties had been identified through field visual inspection of "To Let" advertisements on properties and/or street electric poles near the residential buildings available for rent. Because such types of advertisements at residential areas were widely used as a formal method to provide information for rent at Rajshahi City. However, few properties had also been identified which were advertised for rent having local knowledge from inhabitants of the area during field surveys in the City. Questionnaire surveys have been carried out by the qualified surveyors (mostly, students of the University of Rajshahi). Information regarding residential advertised rent prices and structural attributes had been collected for all properties available for rent during field survey within the specified RCC area. Although 550 properties were originally surveyed by Habib (2004), 55 properties were discarded during geo-coding operation and 16 survey sheets were lacking substantial structural information. Map 3.1 shows the location of sample residential properties and Map 3.2 shows the monthly asking rent of residential properties.

The average usable living area of the sample houses is 1531.96 sq. ft. Number of bedrooms and bathrooms in the houses vary from 1 to 4 and 0 to 3 respectively. The average age of building structures is approximately 19 years (Habib, 2004). Maps 3.3, 3.4, 3.5 and 3.6 show the locations of residential properties with their structural attributes.

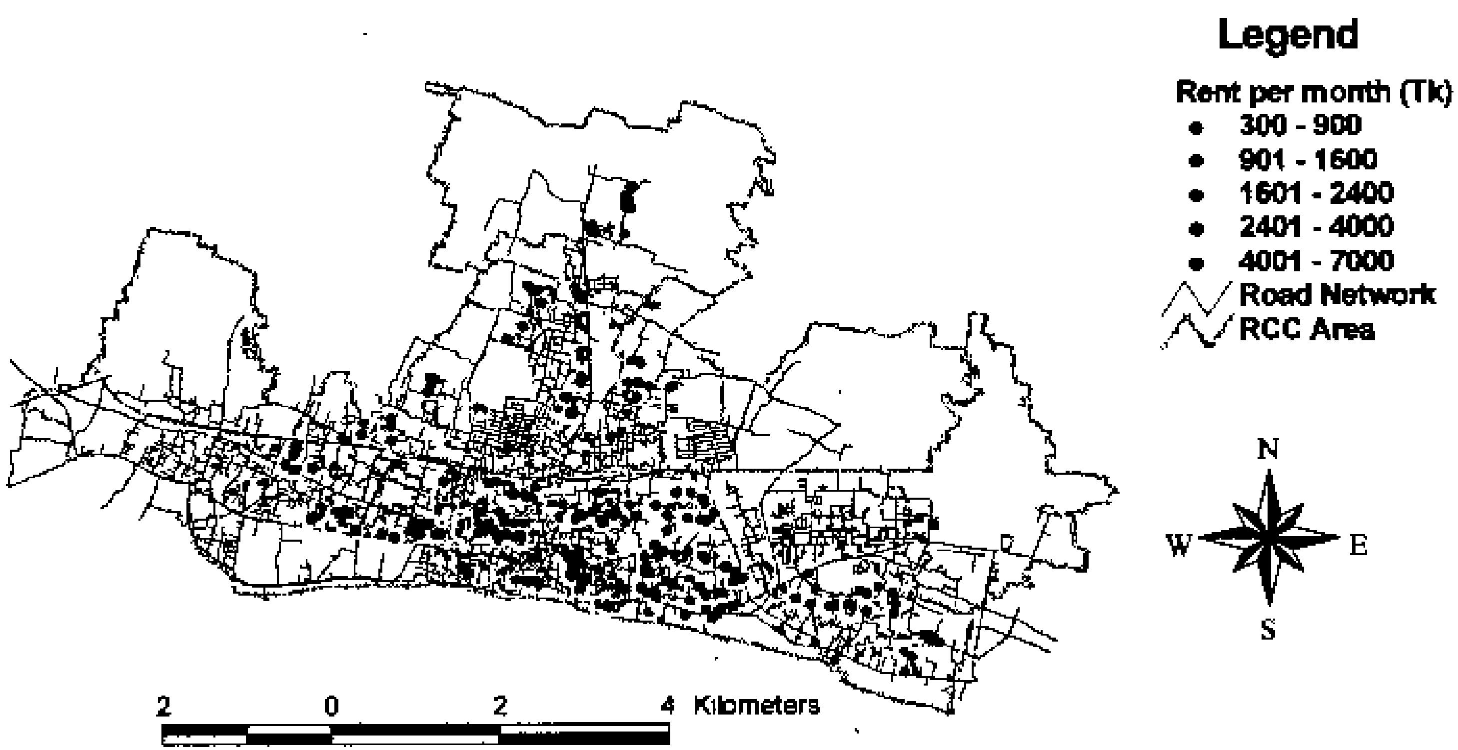
The data for population density was obtained from the Rajshahi Master Plan Project. Map 3.7 shows the population density (persons per acre for the year 2001) by ward which has been prepared with few computational works and assigned to the properties that fall within the respective administrative unit (ward) concerned.

Table 3.1: Description of Variables

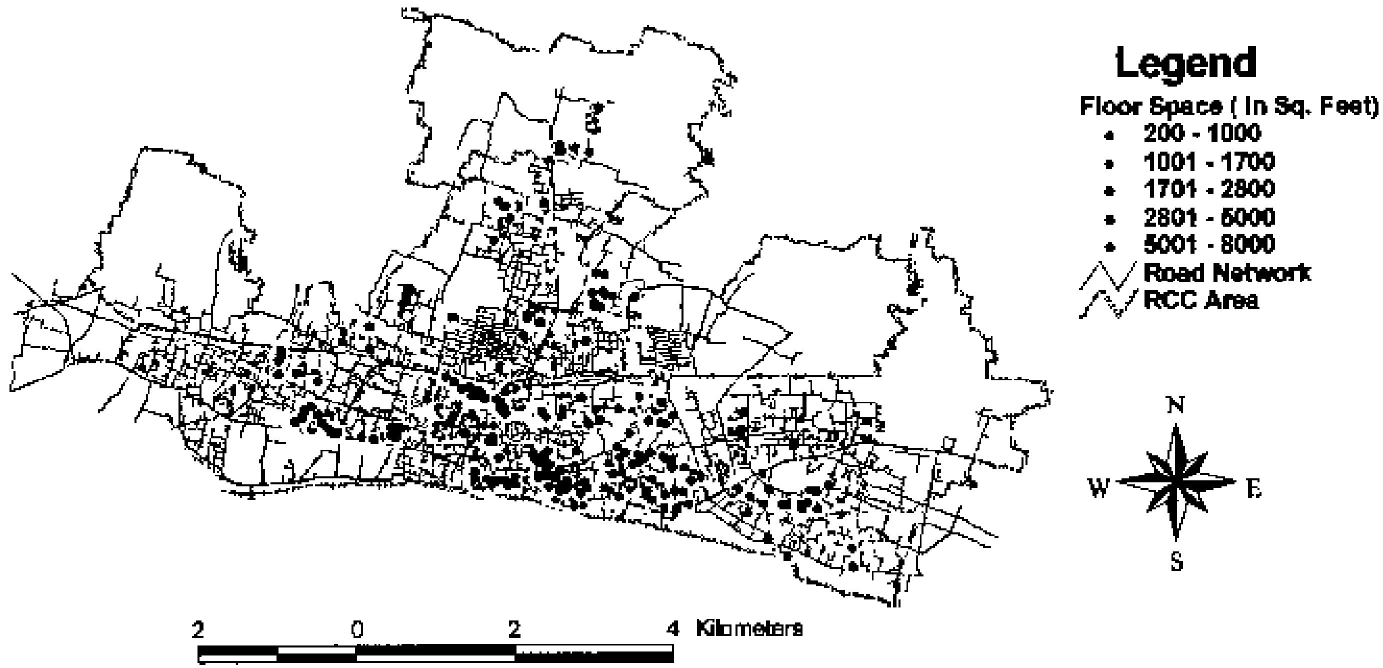
Variable	Definition	Spatial level of data
Measures of Value		
RENT	Rent offered price (Tk.)	Property
Structural attributes		
FL_SPACE	Usable living area (sq. ft)	Property
BEDS	Number of bedrooms	Property
BATHS	Number of bathrooms	Property
BLD_AGE	Age of residential property structure	Property
Neighborhood attributes		
POP_DENS	Population density (persons per acre)	Ward
RES_LUSE	Percentage of area dedicated to residential use	Ward
COM_LUSE	Percentage of area dedicated to commercial use	Ward
COMMU_LU	Percentage of area dedicated to community facilities	Ward
DRAINAGE	Euclidian distance from the property to nearest point of drainage network	Property
Transportation attributes		
M_RD_ACC	Network access distance from property to major roads	Property
CBD_ACC	Network access distance from property to Central Business District (CBD)	Property
W_MAR_AC	Network access distance from property to wholesale markets	Property
EDU_ACC	Network access distance from property to primary school	Property
SHOP_ACC	Network access distance from property to shopping centers	Property



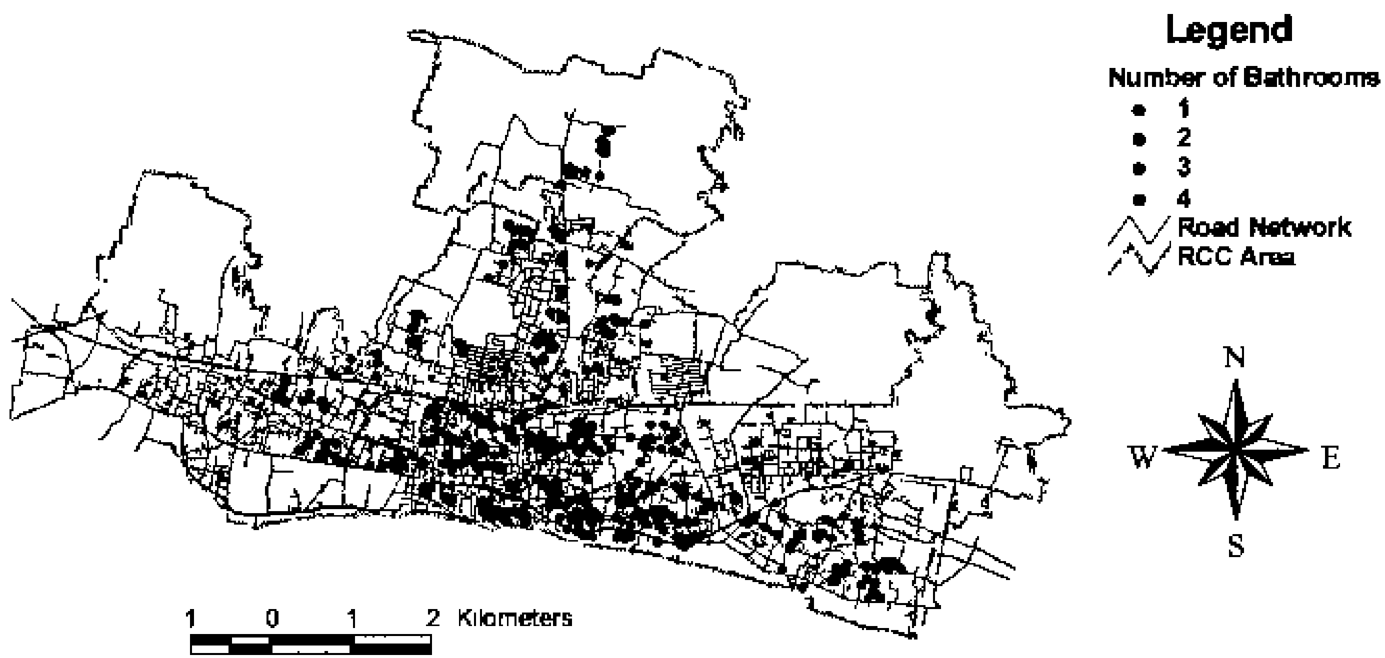
Map 3.1: Location of Sample Residential Properties at Rajshahi City



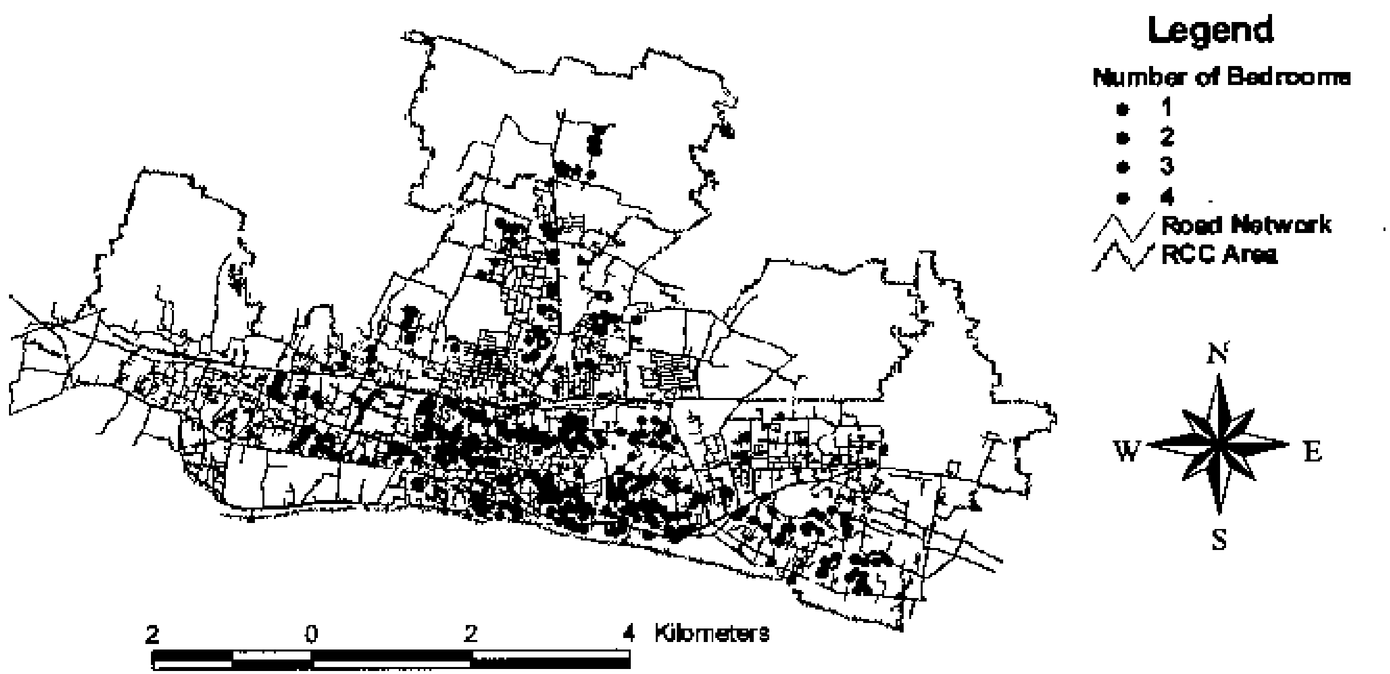
Map 3.2: Residential Properties by Monthly Asking Rent in Taka (May 2004)



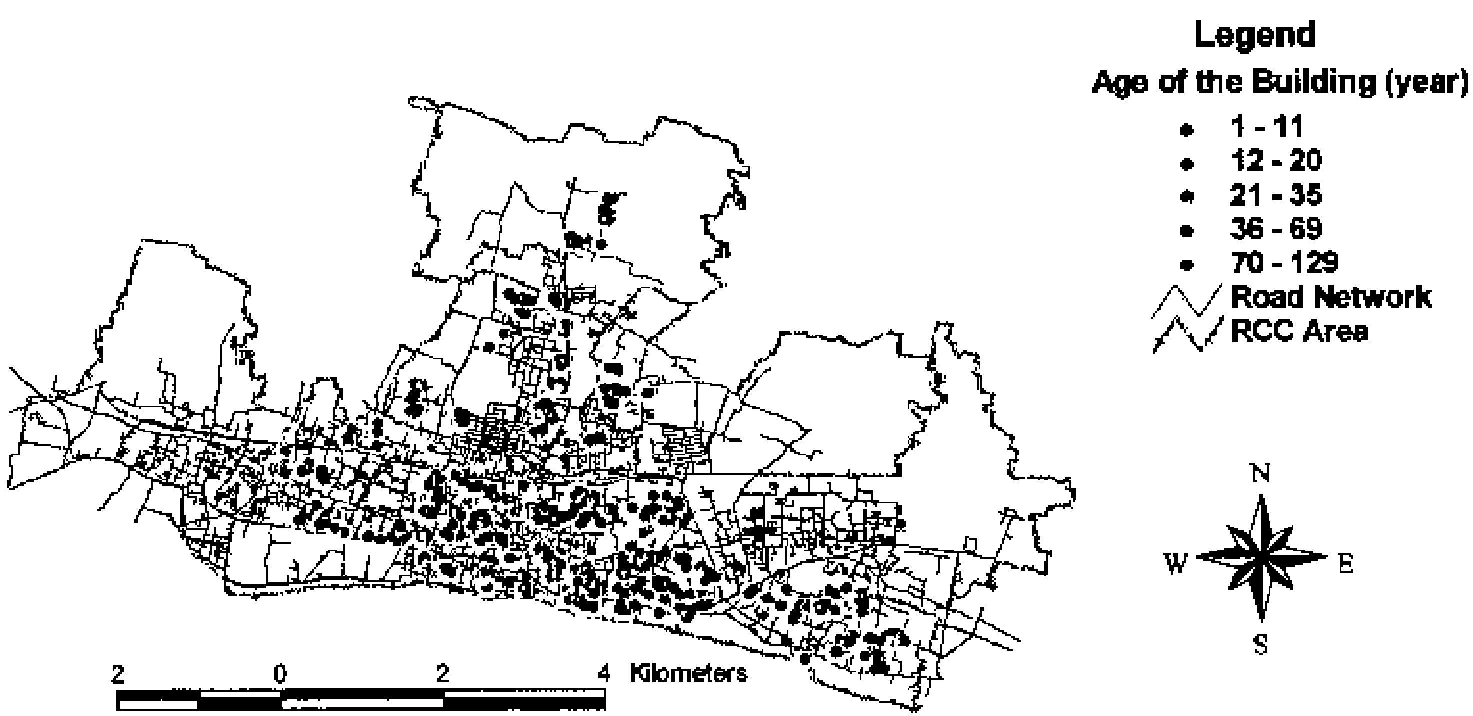
Map 3.3: Residential Properties by Floor Space/ Usable Living Area



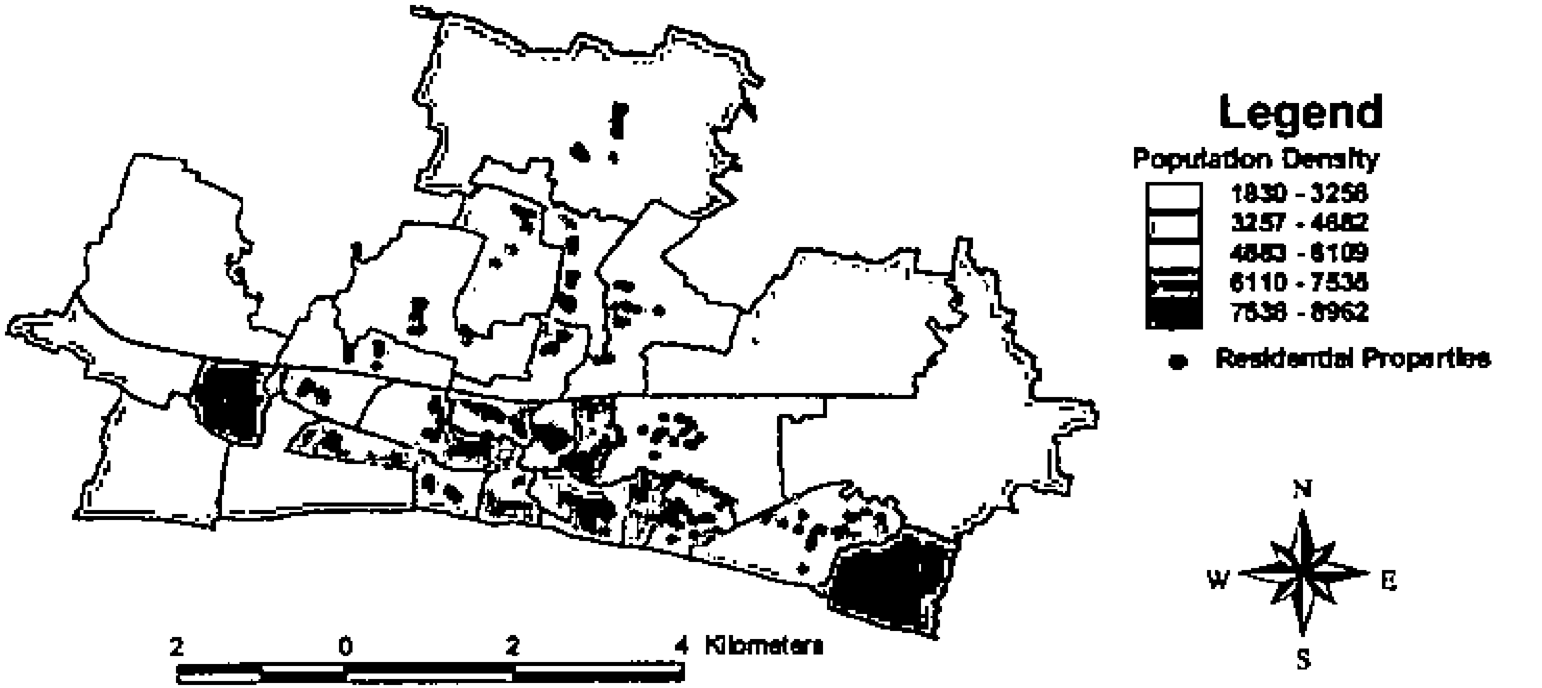
Map 3.4: Residential Properties by Number of Bathrooms



Map 3.5: Residential Properties by Number of Bedrooms



Map 3.6: Residential Properties by Age of Building



Map 3.7: Population Density by Ward and Residential Properties

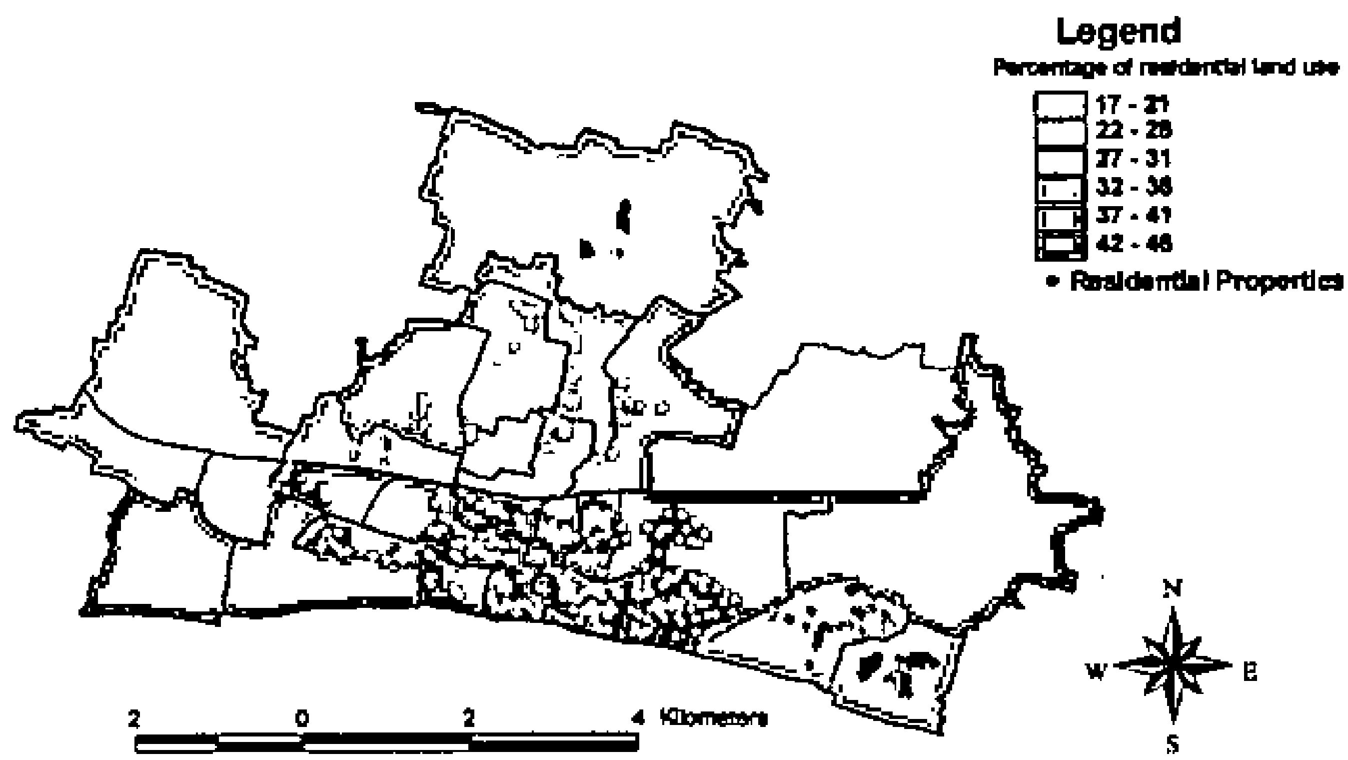
Three types of land use namely residential, commercial and community facilities are considered in this study. The percentage of land use is calculated from the GIS database of Rajshahi Master Plan Project. The percentage share of respective land uses by Strategic Planning Zone (SPZ) defined by Rajshahi Master Plan Project is shown in Table 3.2. All the residential properties are assigned the respective value of the percentage of land uses, which fall within the respective zone (SPZ). Maps 3.8, 3.9 and 3.10 show ward wise percentage share of residential land use, commercial land use and community facilities respectively.

Table 3.2: Percentage share of land uses by SPZ

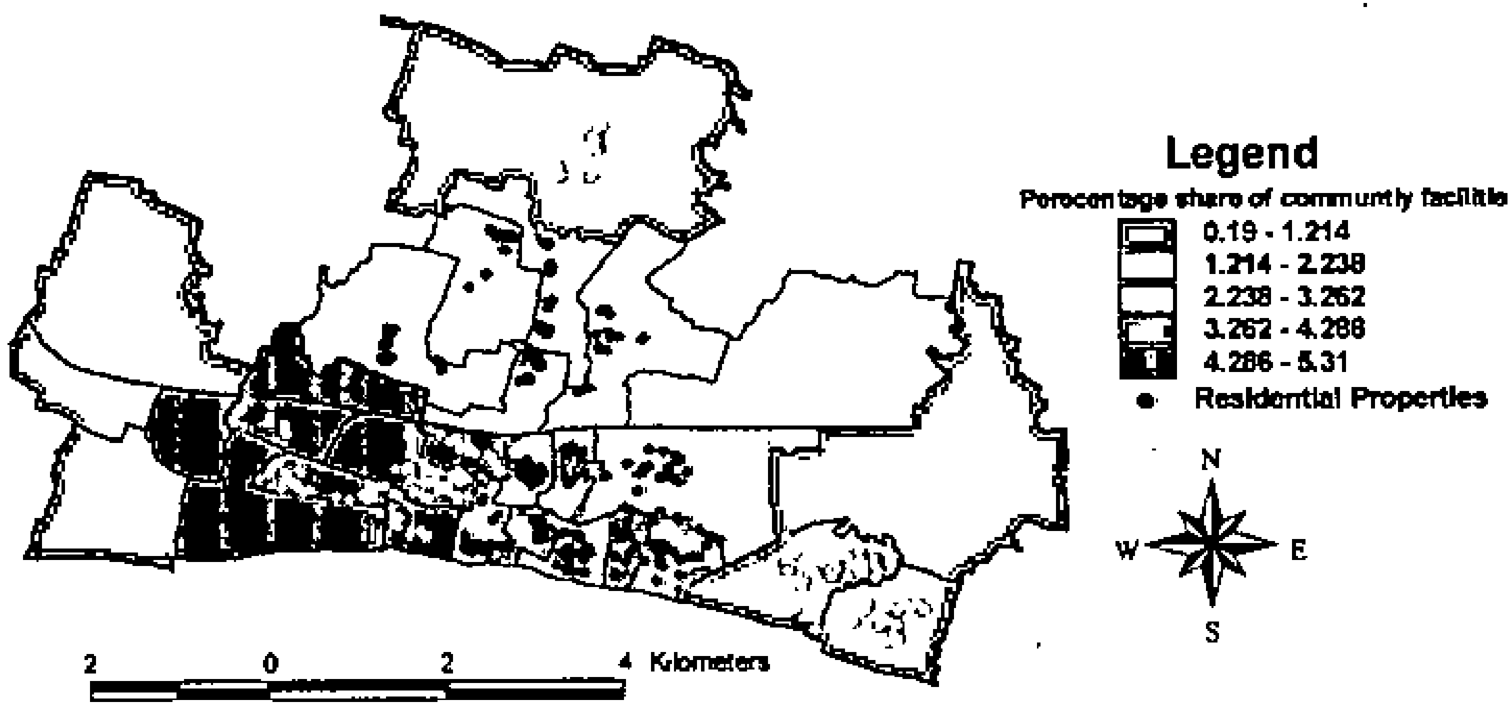
SPZ No	Ward No	Area in acre	Residential (%)	Commercial (%)	Community facilities (%)
8	17	1726.43	27.04	1.76	0.19
13	26	1078.29	16.46	0.43	1.3
14	14, 15, 16, 18, 19 & Cant	2055.54	40.56	1.83	2.21
15	1,2,4	1753.66	31.11	1.65	0.75
17	3, 5, 6, 7, 8, 9, 10, 11, 13	1679.85	45.35	8.63	5.31
18	12, 20, 21, 22, 23, 24, 25, 27	1372.89	43.83	7.69	3.15
19	28, 29, 30	2204.33	28.41	3.54	1.03

Source: Habib, 2004

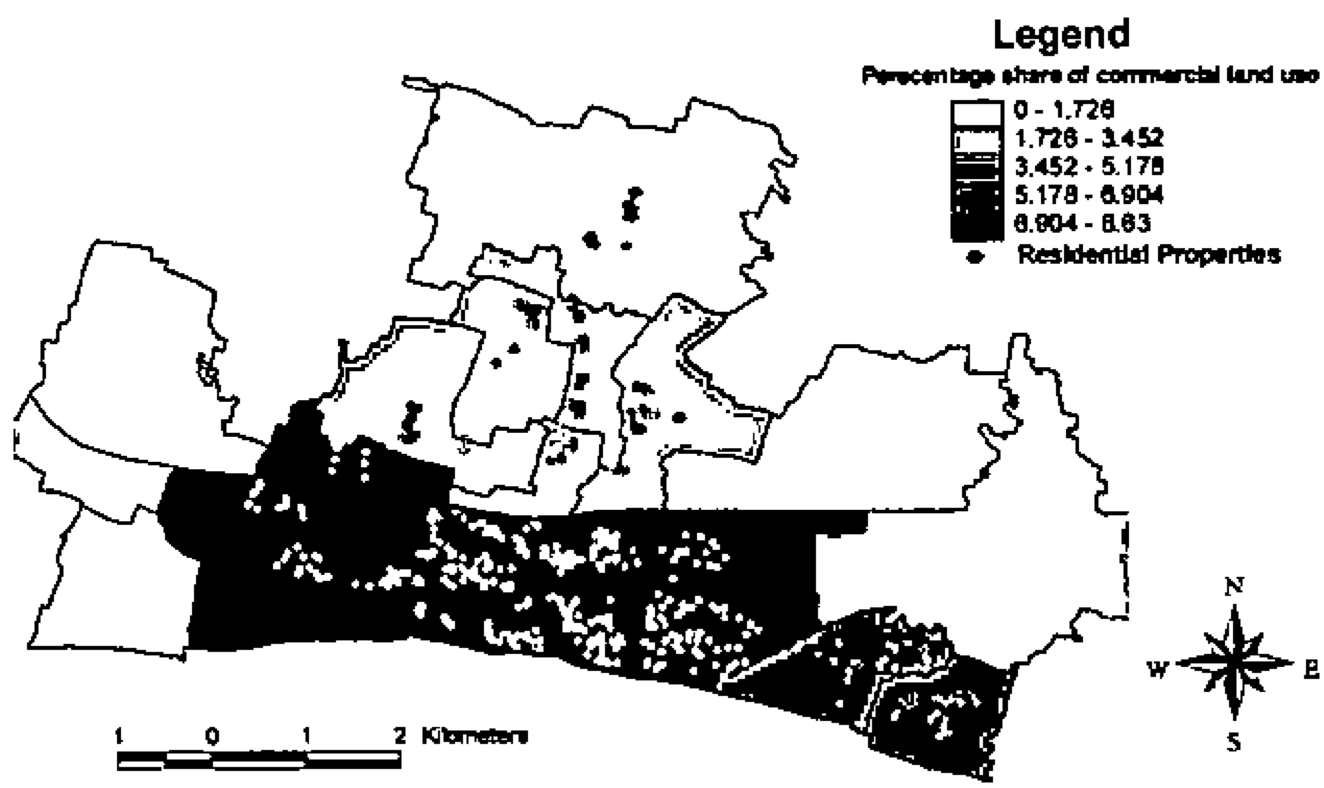
The Saheb Bazar area was considered as the Central Business District (CBD) of Rajshahi City. The area comprises most of the commerce and business centers of the Rajshshai City (Habib, 2004). Map 3.11 shows the point location of the CBD with respect to residential properties. Rani Bazar, Kadirgonj and Saheb Bazar are the major wholesale markets of Rajshahi City (DDC Limited, 2004). Map 3.12 shows the locations of the wholesale markets with respect to the residential properties. The major retail markets and shopping centers of Rajshahi City are New Market, C & B Market, Laxmipur, Upashahar New Market and Horogram markets (Habib, 2004). Map 3.13 shows the location of shopping centers which are considered as shopping centers for this study. The location of primary schools with respect to residential properties is shown in Map 3.14 and Map 3.15 shows the location of residential properties with respect to drainage network.



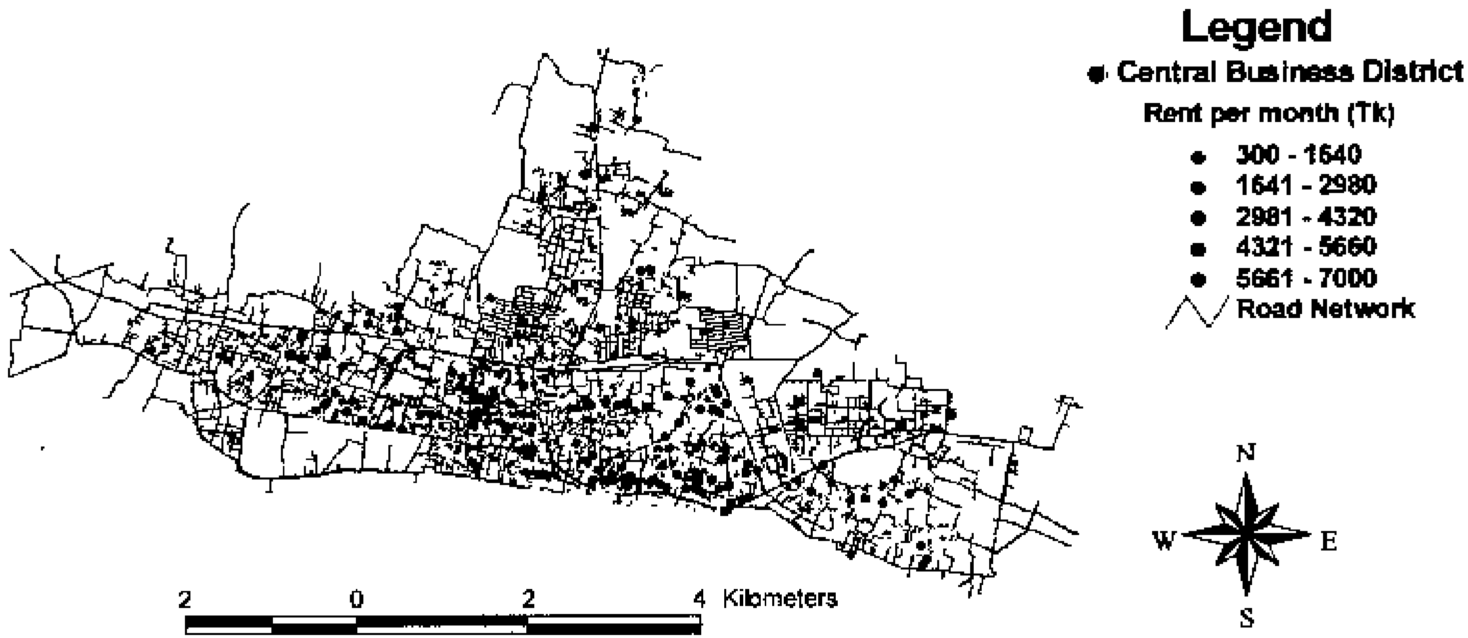
Map 3.8: Percentage Share of Residential Land Use by Ward and Residential Properties



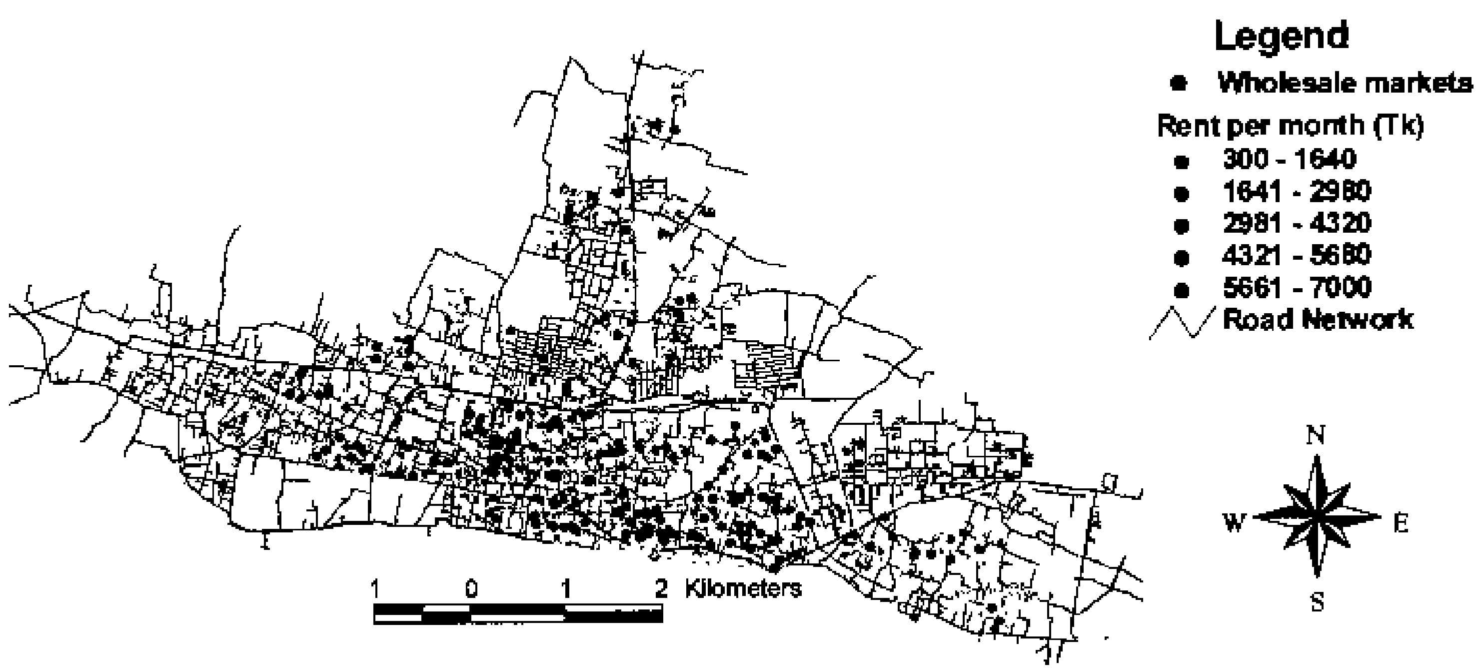
Map 3.9: Percentage Share of Community Facilities by Ward and Residential Properties



Map 3.10: Percentage Share of Commercial Land Use by Ward and Residential Properties

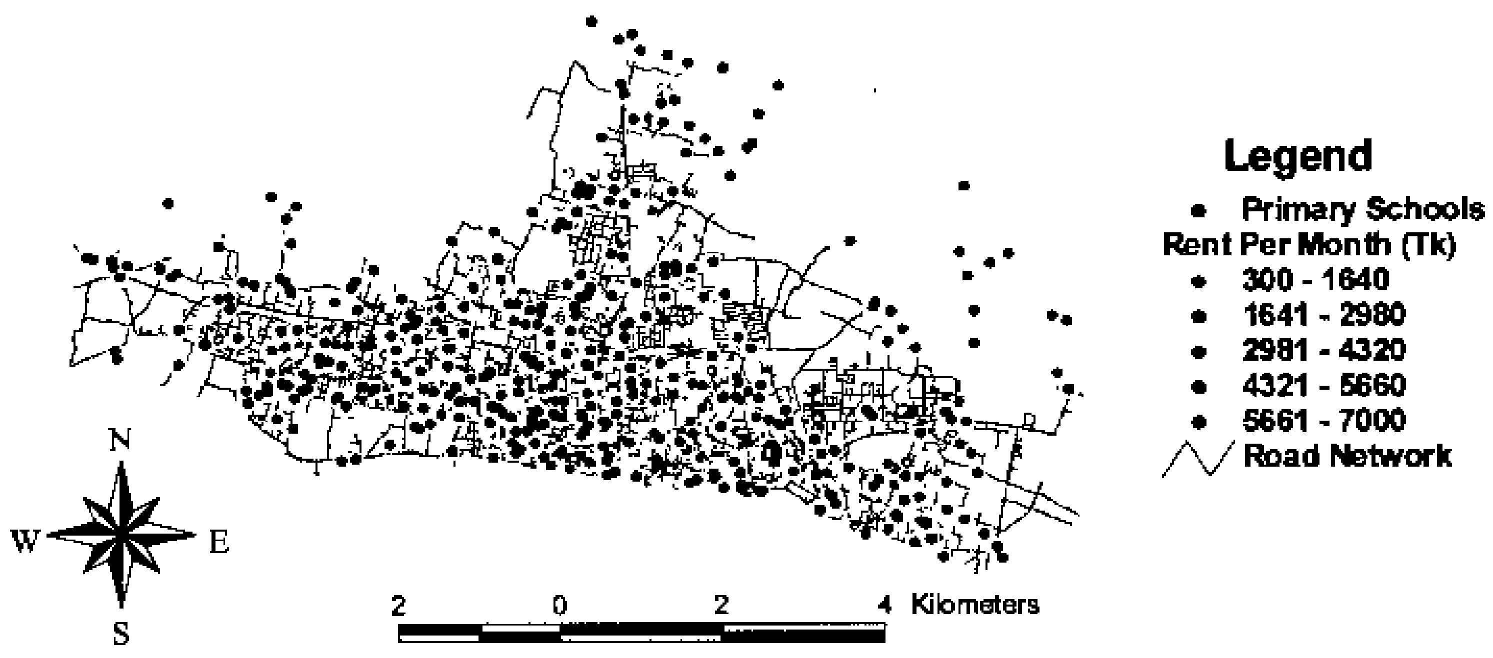


Map 3.11: Location of CBD with respect to Residential Properties

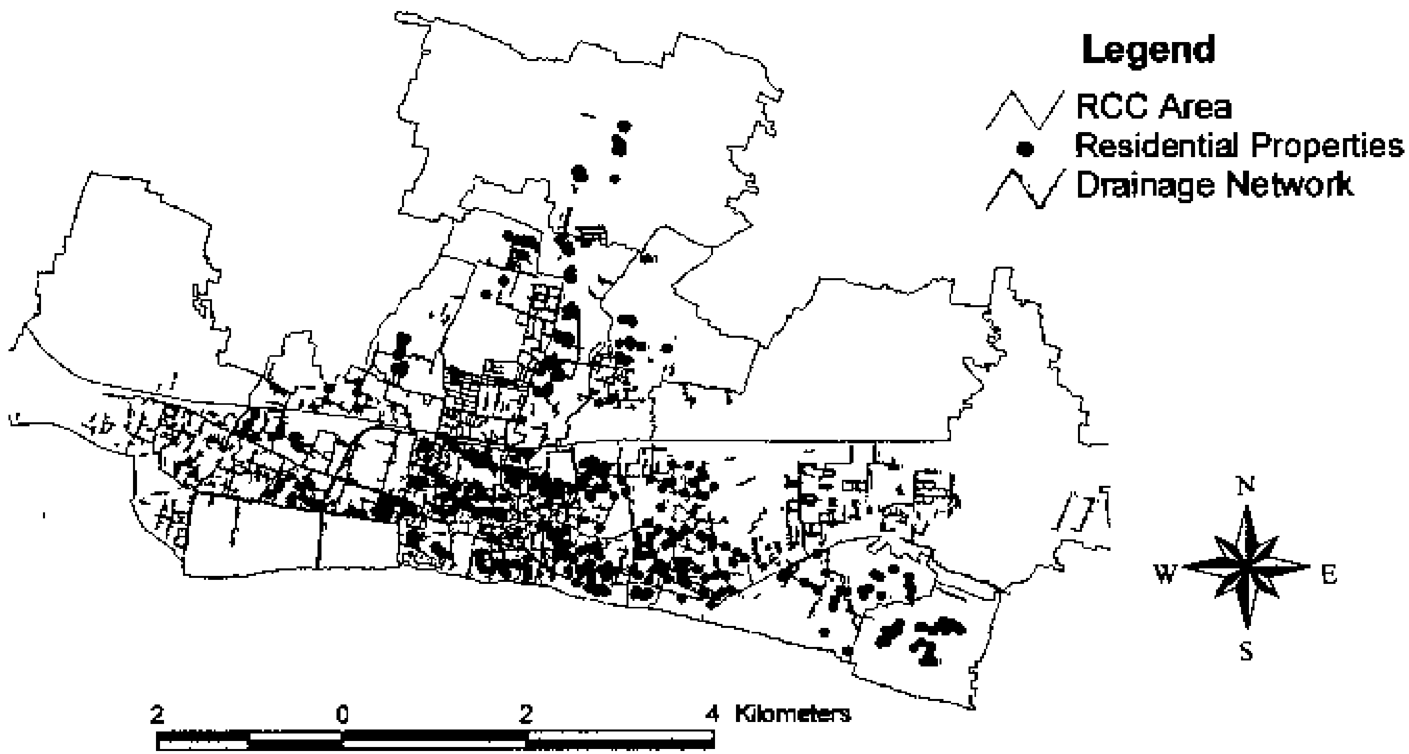


Map 3.12: Location of Wholesale Markets with respect to Residential Properties

Map 3.13: Location of Shopping Centers with respect to Residential Properties



Map 3.14: Location of Primary Schools with respect to Residential Properties



Map 3.15: Drainage Network and Residential Properties

3.5 Summary

The chapter has given an overview of the data which was used to develop ANN model for house rent prediction of Rajshahi City. The data set used to develop the ANN model consists of a sample of 479 single family and multi-family residential properties available for rent. The ANN models in this study have been built using fourteen independent variables. Rajshahi City Corporation area had been selected as a study area of this study which is described in the following chapter.

Chapter 4

STUDY AREA

Chapter 4: Study Area

4.1 Location

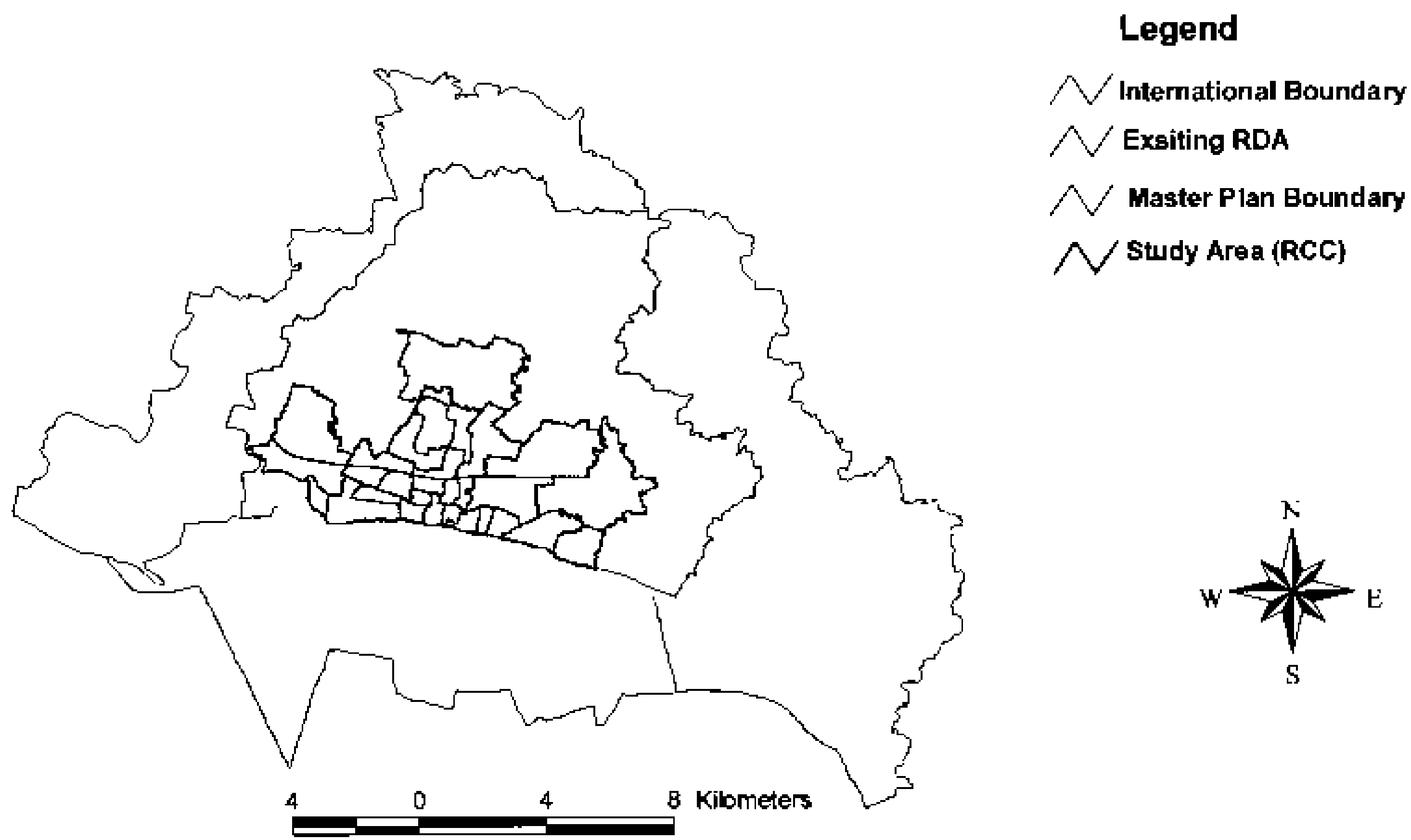
The study area selected for this research is Rajashahi City Corporation (RCC) area. The city is located along the river Padma, between latitude 24°18" N and 24°25" N and longitude 88°33" E and 88°41" E. The area comprises of 51.29 sq. km (19.72 sq. miles) of land with 3.83 lakh population. It is the fourth metropolitan city of the country. The location of the study area in relation to the surrounding areas and administrative units is shown in Map 4.1 and Map 4.2 respectively.

4.2 Historical Background

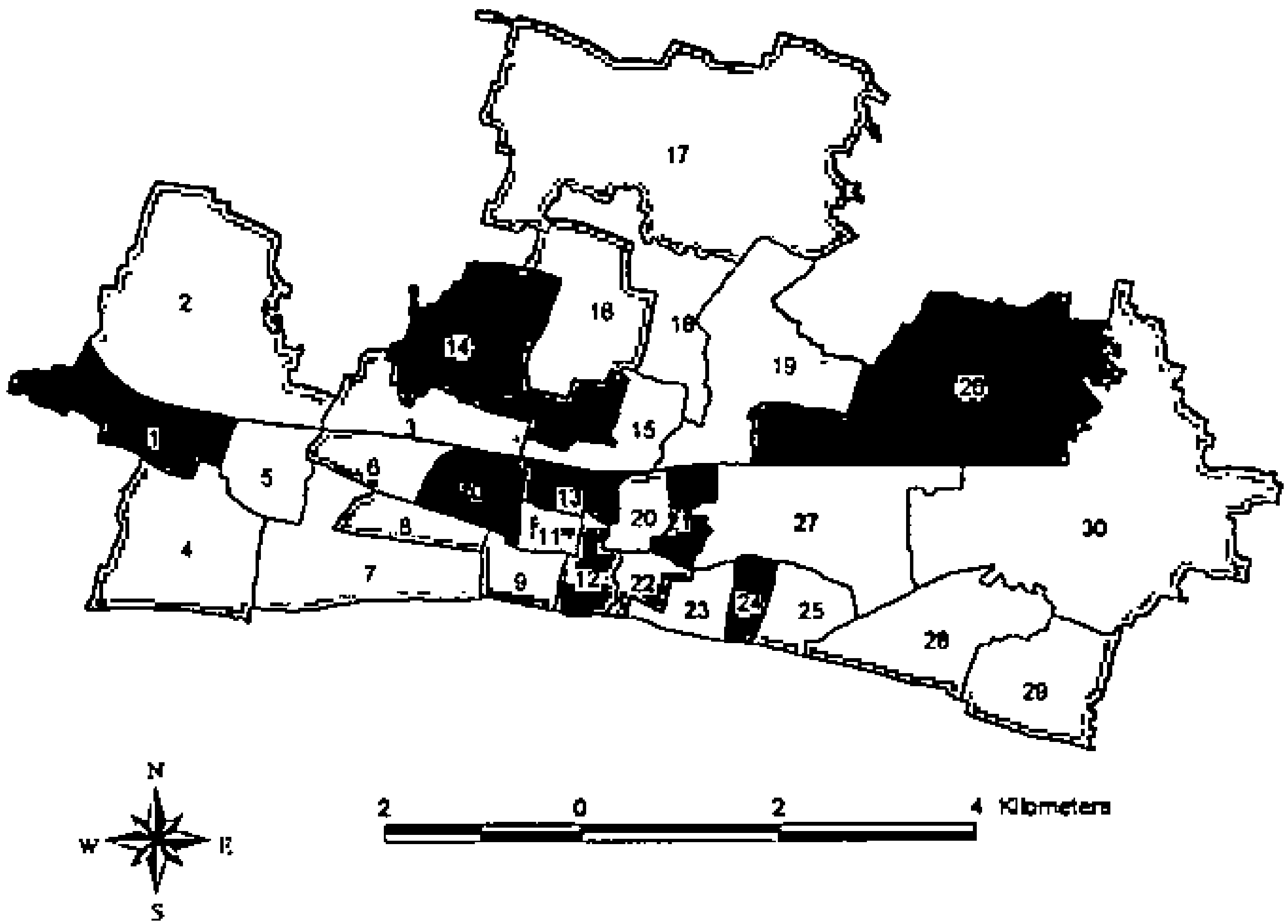
Rajshahi is a divisional city and an important city in the northern region of the country. It was simply a district town prior to 1947 that had become divisional headquarters in 1947. In 1886 during British reign the town gained municipal status and finally achieved the status of City Corporation in 1983. Over the years, it has grown as the administrative headquarters of the Rajshahi Division, and lately flourished as a center of learning. Now it is the 4th largest city in Bangladesh next to Dhaka, Chittagong and Khulna.

4.3 Climate

Rajshahi city has a sub-tropical monsoonal climate. Generally temperature is low in January and varies between 8.8° C to 25.9°C. From February temperature is found to increase up to June and thereafter declines slightly every month from July to August. From September temperature declines rapidly up to January. The people of Rajshahi generally feel the hot-wave during April to May. The mean relative humidity is found to low in March (60.2%) and it is high in August-September (88.4%). High wind speed is observed during April to June. About 77 percent rainfall occurs during June-September and rest 23 percent in the other 8 months.



Map 4.1: Rajshahi City Corporation with Surrounding Areas



Map 4.2: Administrative Units (Wards) of Rajshahi City Corporation

4.4 Land Use Pattern

In the Rajshahi City Corporation area, over 18% land is still being used for agricultural purpose, while about 11% land remains vacant and about 3.52% land belong to char area. Residential use covers about 32%, while road infrastructure covers only 4% of total land.

Water bodies encompass 13.35% that include the Padma River and a large number of ponds. Different educational institutions including Rajshahi Univeristy, Rajshahi University of Engineering and Technology and Rajshahi Medical College encompass about 9% of total area. Industry and commercial land uses together comprise only 4.15% of the RCC land representing the very low profile of economic activities in the City (DDC, 2004).

4.5 Urbanization and Demography

The rate of urbanization and population growth is very low in Rajshahi city compared to other major cities of the country. The popnlation density of the RCC area is only 7,073 persons per sq. km (DDC Limited, 2004).

Presently, the city has a population of 3.83 lakh, which was 2.94 lakh during 1991. In the period of 1981-1991, the population has increased at a rate of 63.36 percent, about 1.14 lakh. However, during 1991-2001, it has increased only 0.88 lakh, accounting for a 30.25 percent rise (DDC Limited, 2004).

The urbanization rate of the northern region (i.e. Rajshahi Division) remained the same throughout the last decade, which was 17.3 percent. The country's annual growth rate of population in the period 1991-2001 was the lowest in Rajshahi SMA (1.87 percent) and fastest in Dhaka SMA (4.26 percent). Every year the capital city Dhaka absorbs an additional population equivalent to the current population of RCC area (DDC Limited, 2004).

4.6 Economy and Employment

Rajshahi presents a case of quasi-urbanization. Its inadequate development of infrastructure facilities, shortage of capital and absence of entrepreneurs are constraints to development of economic base of the city. Its hinterland is predominantly agrarian in character (DDC Limited, 2004).

A few major scattered industries, public sector organizations, academic institutions, informal sector and trade and commerce provide major base for economic activities in the study area. Four growth centers and 12 major hats/bazaars in and around study area exert profound impact on the study area. Informal sector accounts for 19% of total employment in the study area whereas Trade and commerce provides employment for 33.47% of labour force. Other important sectors of employment are Administration and Service (22.37%), farm activities (10.12%) and Non-farm wage labour (13.38%).

Majority of households (61%) of the study area belong to monthly income group of 2,500-6,500 and savings by households are comparatively low in the study area. Labour force in the study area will increase from 299.89 thousand in 2001 to 385.67 thousand in 2021. About 27% of labour force will not find job, if current development trends continue (DDC Limited, 2004).

The city of Rajshahi acts as major employment centre for rural poor and destitutes migrating form its hinterlands. The city provides the base and facilities for industrial and manufacturing activities at a moderate level, and generates various kinds of services in both public and private sectors. It is modal point for transport network and transshipment activities for the adjoining regions and with other parts of the country.

4.7 Transportation

The city of Rajshahi had only a modest growth during the last two decades. In the national context, Rajshahi is well connected with rest of the country by both road and rail. The broad gauge railway line from Rohanpur to Ishurdi, with a link to Chapai-Nowabganj passes through the heart of Rajshahi city and forms part of the main broad gauge system in the country. With the opening of Nalka-Hati Kamrul-Bonpara road, Dhaka is only 5 hours away from the study area. The situation has further improved with the completion of the approach road to Jamuna Bridge through Tangail.

The traffic study conducted in 2002 indicated that none of the major roads in the study area has had any capacity constraints in terms of peak hour flow viz-z-viz design capacity. An Origin-Destination (O-D) survey indicated that 73 to 74% of all incoming and outgoing traffic had the destination or origin within the study area.

In the study area 55% OF daily trips are made by rickshaws/vans and cycles, while another 29% are made on foot. Most the trips (69%) of the study area are related to either home or work, leaving another 15% which are made to schools/college and universities.

4.8 Housing Situation

In the study area most of the housing units (over 90%) come from informal private sources. The NGOs usually operate in low-income communities in rural areas providing finance and services only.

About 44 percent of the households become landowners through inheritance, while over 44% became owners by way of purchase. Land value in the Rajshahi City is very low compared with Dhaka and Khulna. In spontaneous housing areas of the main city land sells between Tk. 90 thousands to Tk. 120 thousands per katha. Land value in planned areas varies between Tk. 100 thousands to Tk.120 thousands per katha. In the study area there is a housing backlog of 1553 units (1991).

4.9 Market and Shopping Facilities

There are 8 daily bazars in Rajshahi city to serve its 3 lakh 83 thousand population (2001). However, the bazars are not evenly distributed over the city to serve all its inhabitants efficiently. Besides daily markets, the city has a few shopping centers like New Market and Shaheb Bazar. There are also some wholesale markets namely Shaheb Bazar, Kadirganj Bazar and Rani Bazar etc. in the study area.

4.10 Recreational Facilities

With easy access to satellite TV channels served by cable operators, cinema has lost its attraction in the study area. In Rjshahi City, presently there exist seven cinema halls. Satellite TV channels are possibly most popular and the cheapest means of indoor recreation. The upper income groups of society enjoy their leisure time in clubs. There are a number of clubs in the city. But most of them are for professional people, like Police Club, Jilkahana club, University Club, Doctors' club. There are very few parks and playgrounds in Rajshahi City. There are only three parks which is very inadequate for the city. Estimation shows that RCC area has only 0.41 acres of open space per thousand populations which is very low compared to other major cities (DDC Limited, 2004).

4.11 Postal Facilities

There are 17 post offices within the RCC area. About 30% of these were established during the period of 80s. However, the existing post offices are not well distributed over the city. Among 30 RCC words only 15 have Post offices. There are 74 post boxes placed at different important locations of the city for collection of letters.

4.12 Municipal Services

4.12.1 Water supply

There are 785 community water stand posts and 85 on-street *dhop* water stands in the city. There are also 3,750 hand tube wells for drinking water supply. The city has eight overhead tanks and three water treatment plants. Ground water is extracted by 45 production tube wells. Till 1995 there were 182 km of water pipelines in the city.

4.12.2 Solid waste management

The city dwellers generate about 200 m. tons of solid waste daily. RCC collects about 142 m. tons of solid waste, the rest littered around. RCC has 17 motorized and 126 non-motorized transports to carry solid waste with 934 staff of different categories engaged in solid waste collection and disposal. Presently there is only one dumping site for the city's solid waste located at Bonogram, Nawdapara. The number of dustbins available is inadequate for the city. RCC does not collect waste from households.

4.12.3 Sanitation and public toilet

According to RCC sources, about 50 percent of the RCC area households have sanitary latrine facilities, of them 30% have latrine with soak pit and 20% have latrines without soak pit. There are about 43 pubic toilets in the city at important public locations.

4.13 Summary

This chapter carries out brief description of the study area. Rajshahi City Corporation (RCC) area was selected as a study area for this research. Rajshahi is a divisional city and it is the fourth metropolitan city of the country. Residential use covers highest percentage of land of the study area followed by agricultural land use. The rate of urbanization and population growth is comparatively lower in Rajshahi City. The ANN model was developed using the variable data collected from the study area. The development procedure of ANN model and result of the model is discussed in the following chapter.

Chapter 5

DETERMINATION OF ARTIFICIAL NEURAL NETWORK MODEL

Chapter 5: Determination of Artificial Neural Network Model

5.1 Introduction

To address the issue of application of Artificial Neural Network (ANN) in house rent prediction, this chapter illustrates the development procedure of ANN model for house rent prediction of Rajshahi City and discusses the results of the developed model. This chapter attempts to identify some of the independent variables which influence the house rent of Rajshahi City based on the relative influence factor of different attributes. The chapter will also focus on the analysis of elasticity.

5.2 Development of Artificial Neural Network Model

For developing the artificial neural network (ANN) model the relevant data set was separated into two separate subsets namely the "training set" and the "production set". The training set was used to train the neural network model and the production set was used to test the model's performance. The data set used to develop the Neural Network Model consists of a sample of 479 single family and multi-family residential properties available for rent in Rajshahi City. The two samples were created by first sorting the houses by location, then by rent and then by picking every fourth house for the production set. The developed model was trained with 360 residential properties (training set) and their predictability in estimating value was tested with the remaining 119 residential properties (production set). The neural network model built for this data set utilized the following fourteen independent variables: usable living area (FL_SPACE), number of bedrooms (BEDS), number of bathrooms (BATHS), age of residential property structure (BLD_AGE), population density (POP_DENS), percentage of area dedicated to residential use (RES_LUSE), percentage of area dedicated to commercial use (COM_LUSE), percentage of area dedicated to community facilities (COMMU_LU), Euclidian distance from the property to nearest point of drainage network (DRAINAGE), network access distance from property to major roads (M_RD_ACC), network access distance from property to central business district (CBD)(CBD_ACC), network access distance from property to wholesale markets (W_MAR_AC), network access distance from property to primary school (EDU_ACC), network access distance from property to shopping centers (SHOP_ACC). Table 5.1 details the descriptive statistics of the entire sample and the two subsets for training and testing. From Table 5.1 it can be seen that there were no significant differences between the training and testing data subsets and each is a fair representation of the entire data set.

Table 5.1 Descriptive statistics of entire sample, training set and testing set

Variables	Mean			Maximum			Minimum		
	Entire Sample (479)	Training Set (360)	Testing Set (119)	Entire Sample	Training Set	Testing Set	Entire Sample	Training Set	Testing Set
RENT	1961.9	1936.2	2039.5	7000.0	7000.0	6000.0	300.0	300.0	300.0
FL_SPACE	1532.0	1509.3	1600.6	8000.0	7000.0	8000 0	200.0	200.0	300.0
BEDS	2 6	2 6	2.7	4.0	4.0	4.0	1.0	1.0	1.0
BATHS	1.5	1.5	1.5	3.0	3.0	3.0	0 0	0.0	1.0
BLD_AGE	18.6	18.9	17.7	129.0	129.0	94.0	1.0	1.0	2.0
POP_DENS	64.6	64.7	64.5	161.7	161.7	161.7	7.4	7.4	7.4
RES_LUSE	41.2	41.2	41.2	45.4	45.4	45.4	27.0	27.0	27.0
COM_LUSE	6.0	6.0	5.9	8.6	8.6	8.6	1.4	1 4	1.4
COMMU_LU	3.1	3.1	3.1	5.3	5.3	5.3	0.2	0.2	0 2
DRAINAGE	62 7	61.8	65.4	760.1	733.9	760 1	1.3	1.3	2.5
M_RD_ACC	920.0	926.6	899.8	2871.5	2871.5	2663.7	48.8	48.8	175.0
CBD_ACC	2302.3	2305.5	2292 5	5603.6	5603.6	5503.3	207.5	278.8	207.5
W_MAR_AC	1927.0	1933.0	1908.7	5603.4	5603.4	5395.7	82.1	82 1	183.4
EDU_ACC	919.3	923.1	907.8	17775.6	17775.6	2613.5	3.1	3.1	21.7
SHOP_ACC	1771.1	1782.7	1735.9	5691.1	5691.1	5483.3	88.3	88.3	114.6

5.2.1 Initial model

To develop the neural network model a back-propagation neural network software package, *NeuroShell* (Ward Systems Group, Inc), was used. The neural network results that are reported in this study are the "best" results that were obtained after many different trials. The "best" results were defined as:

1) The model that predicted the highest percentage of houses with average absolute errors below 5%

2) The model that possesses the lowest percentage of mean absolute error and
3) The model that had the highest value the network performance statistic which is better known as R^2 or the coefficient of multiple determinations.

The R^2 is the same statistical indicator which is usually applied to multiple regression analysis. It compares the accuracy of the model to the accuracy of a trivial benchmark model wherein the prediction is just the average of all of the example output values. This R^2 value is also used in the later chapter for comparing the prediction performance of ANN model and hedonic price model.

The problem was to determine the optimal number of hidden layers and the optimal number of nodes to use in each hidden layer for developing the "best" neural network model. The only method available to do this is through trial and error (Worzala et al, 1995). Therefore, in this study a trial and error process was applied to find the optimal artificial neural network model. In this process, seventeen hidden neurons were found to be the optimal number of neurons within the hidden layer for the best ANN model. Table 5.2 details the results of the seven ANN models created during this procedure. The network model created with 17 hidden neurons exhibited superiority in all three performance criteria.

Table 5.2: Alternative ANN models varying the number of hidden neurons

Model	Number of hidden neurons	R^2	Percentage mean absolute error	Percentage of houses < 5% absolute error
1[a]	17	0.5967	24.6	13.45
2	25	0.5593	25.1	12.6
3	35	0.5589	25.1	12.6
4	43	0.5591	25.1	11.76
5	53	0.5575	25.1	13.45
6	65	0.5588	25.1	13.45
7	78	0.5563	24.9	12.6

Note: [a] Indicates the best results

Figure 5.1 shows the neural network structure of the house rent prediction model. The result of the model is shown in Figure 5.2 and Figure 5.3 shows the actual and predicted rent for 119 test properties.

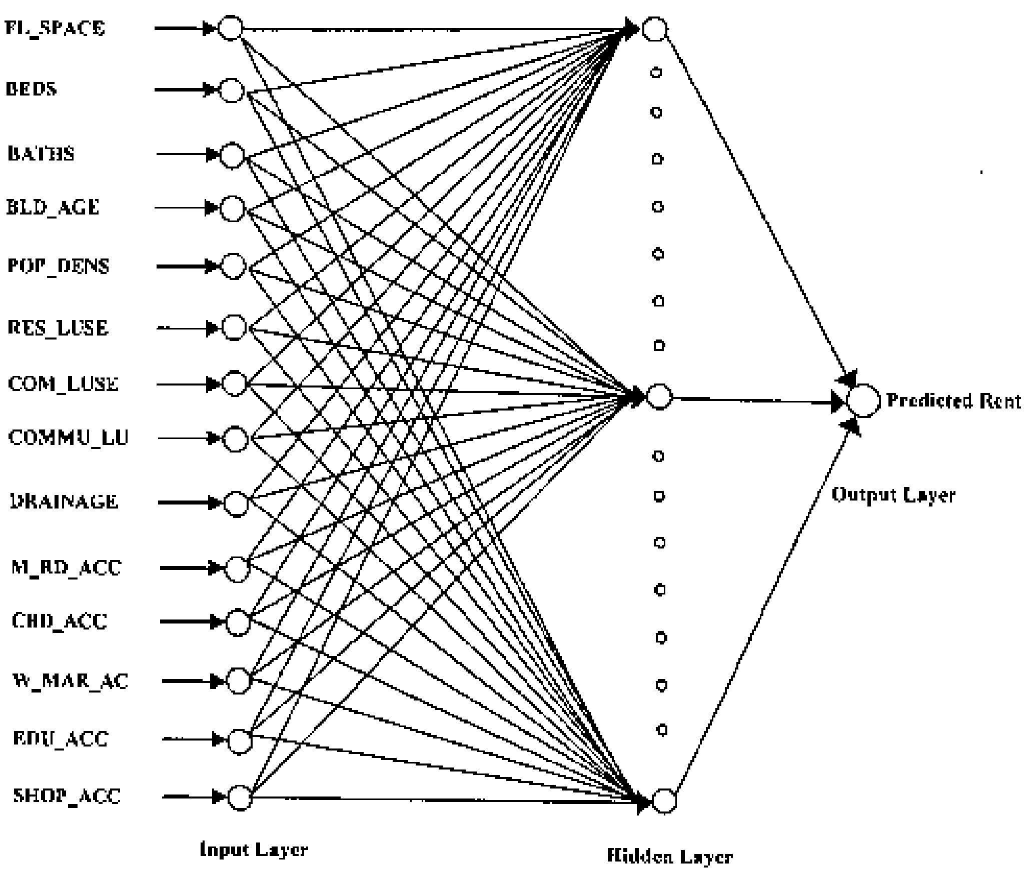


Figure 5.1: Neural Network Structure of House Rent Prediction Model

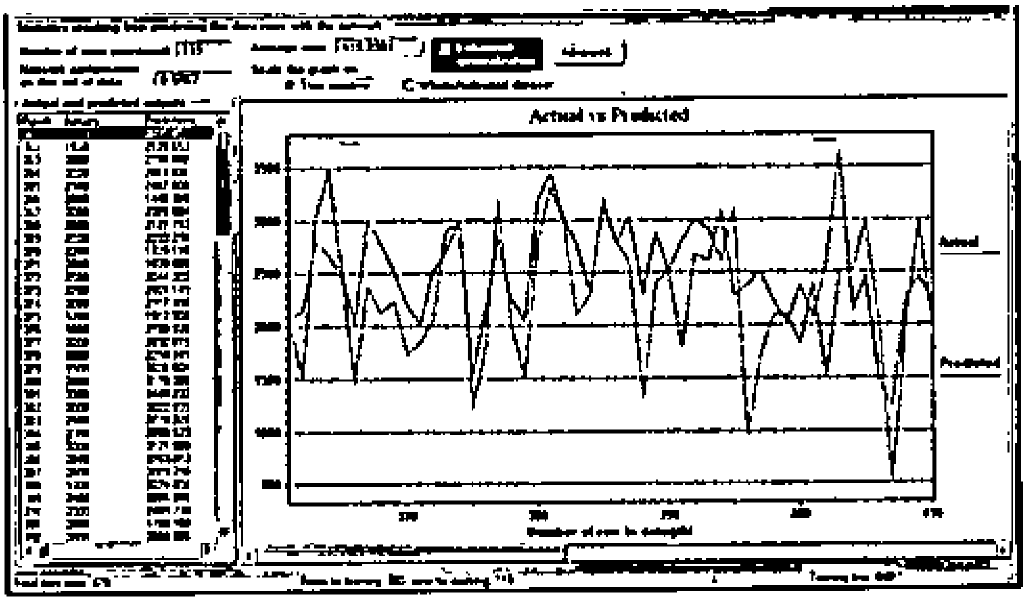


Figure 5.2: Initial neural network model

From Figure 5.2 it is seen that the network performance statistic is better known as R^2 or the coefficient of multiple determinations value of this model was 0.5967. From Figure 5.3 it can be observed that the lines of actual and predicted values are fairly close. The model had a mean absolute error of 24.6% and it predicted 13.45% residential property with average absolute error below 5%.

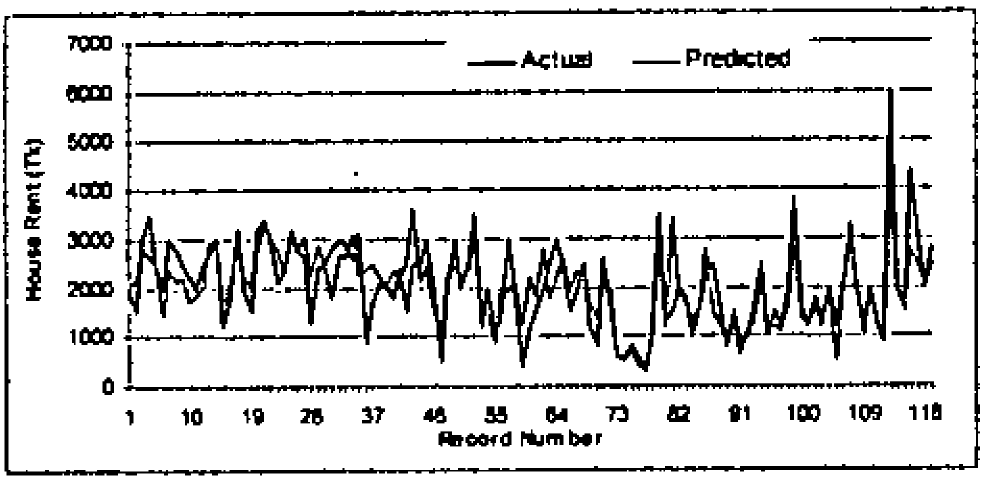


Figure 5.3: Actual and predicted house rent of test sample.

5.2.1.1 Relative Importance of Inputs

The importance of input values are a relative measure of how significant each of the inputs is in the predictive model whose weights range from 0 to 1. Higher values are associated with more important variables (inputs). The relative contribution factors of different inputs for the initial neural network model (the relative importance of inputs) are given in Table 5.3.

Table 5.3: Relative importance value of inputs

Variable	Relative Importaoce value
CBD_ACC	0.387
COM_LUSE	0.155
RES_LUSE	0.119
COMMU_LU	0.061
FL_SPACE	0.055
DRAINAGE	0.051
POP_DENS	0.043
BATHS	0.036
SHOP_ACC	0.028
BEDS	0.027
EDU_ACC	0.019
W_MAR_AC	0.009
M_RD_ACC	0.007
BLD_AGE	0.003

The relative contribution factor shows that network access distance from property to central business district (CBD_ACC), percentage of area dedicated to commercial use (COM_LUSE), percentage of area dedicated to residential use (RES_LUSE) are important factors that determine the residential property rent of Rajshahi City whereas network access distance from property to major roads and age of the residential property structure are the less important factors (Figure 5.4). Community facilities has a relatively high impact on house rent compared to usable living area, population density, number of bathrooms, number of bedrooms and amenities around the house area. The result indicates that neighborhood attributes play an important role in house rent determination in Rajshahi City.

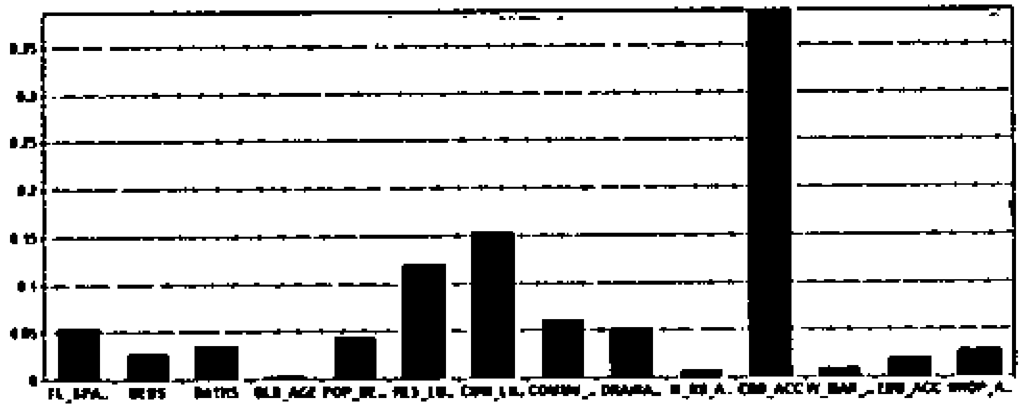


Figure 5.4: Relative Importance of Inputs

5.2.2 Best neural network model

To develop a better neural network model it was decided to eliminate the inputs with low contribution from the model. To do this all the variables with a relative importance value below 0.02 were removed from the model. From the initial model four variables (EDU_ACC, W_MAR_AC, M_RD_ACC, and BLD_AGE) were removed. With the rest of the ten variables the model was trained again. The same trial and error method was used to obtain the best results. Table 5.4 details the results of the seven ANN models created during this procedure. The network model created with 80 hidden neurons exhibited superiority in all three performance criteria.

Table 5.4: Alternative ANN models varying the number of hidden neurons

Model	Number of hidden neurons	R^2	Percentage mean absolute error	Percentage of houses < 5% absolute error
1[a]	80	0.621	22.52	14.28
2	54	0.4953	26.12	11.76
3	14	0.6183	25.15	12.61
4	43	0.5649	25.09	12.61
5	65	0.6065	23.98	13.45
6	31	0.563	25.12	14.29
7	26	0.5632	25.12	14.29

Note: [a] Indicates the best results

The predicting result of new developed model is given in Figure 5.5 and Figure 5.6 shows the actual and predicted house rent for 119 test properties for two ANN models (The data used for Figure 5.6 have been sorted in ascending actual property value). The R^2 value of the new model is 62.10% which is higher than the initial model (59.67%). So the new model can predict the house rent more accurately than the previous one. Table 5.5 illustrates the results of two models. Second neural network model had a mean absolute error of 22.52% while the initial model had 24.61% which would indicate that the second model was a better model for predicting house rent. The maximum absolute error test showed that the second model outperformed the initial model (157.55% compared to 214.23%). Moreover, Figure 5.5 gives the evidence of improvement in accuracy using the new model over the initial model.

Table 5.5: Comparison of predictive power of two ANN models

Model	Mean Absolute Error (%)	Maximum Absolute Error (%)	Error below 5% (%)	R^2
Neural Network Model	24.61	214.23	13.45	0.5967
Best Neural Network Model	22.52	157.55	14.28	0.6210

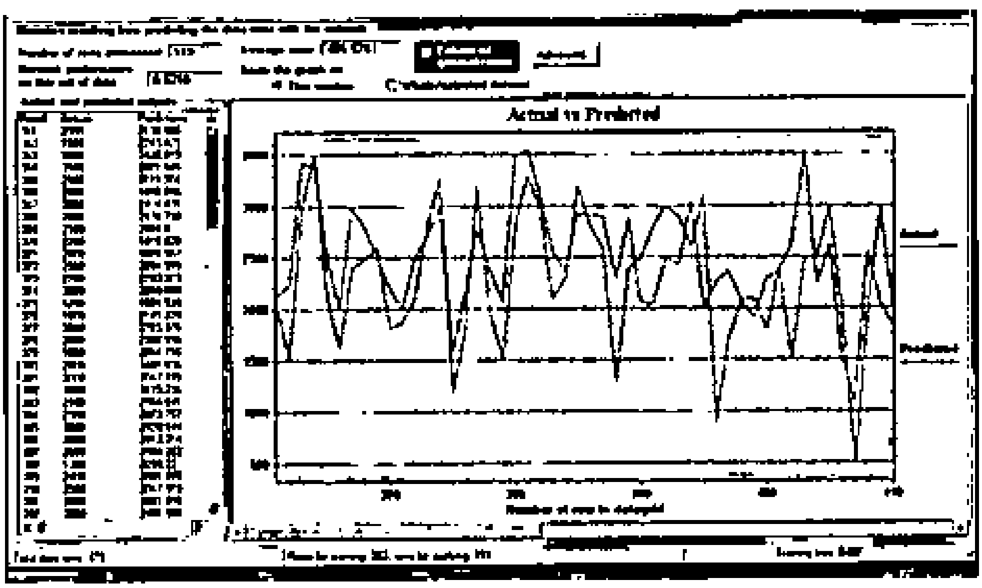


Figure 5.5: Best ANN model

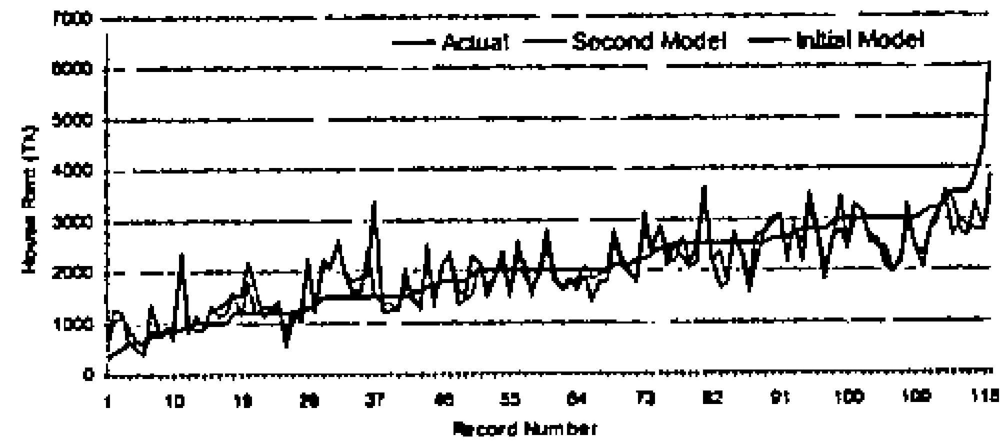


Figure 5.6: Actual and Predicted house rent

5.2.2.1 Relative Importance of Inputs

In the second model the relative importance of inputs has been changed from the initial neural network model. From Figure 5.7, it can be seen that percentage of area dedicated to community facilities and percentage of area dedicated to commercial use became important factors in determining house rent in Rajshahi city whereas usable living area had very little importance. In both models it is seen that land use plays a very important role in determining house rent in Rajshahi City.

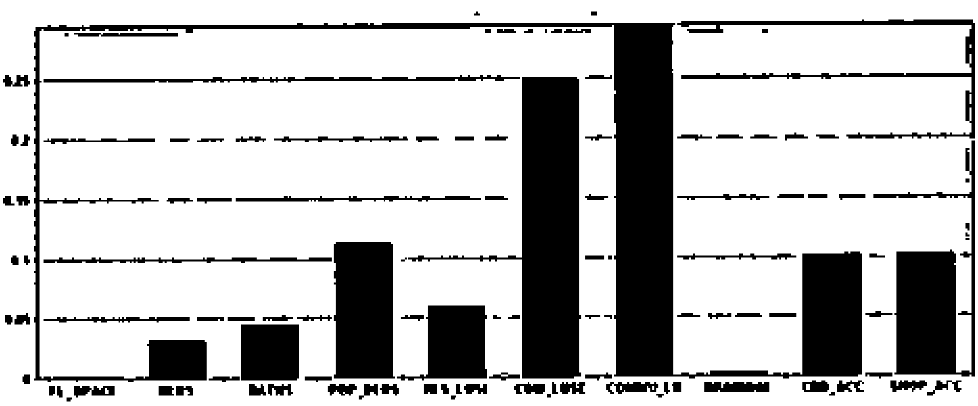


Figure 5.7: Relative importance of inputs in best ANN model

5.3 Elasticity Estimation

Elasticity is the percentage change of house rent with the changes of independent variables. Elasticity of house rent with respect to different independent variables has been discussed below.

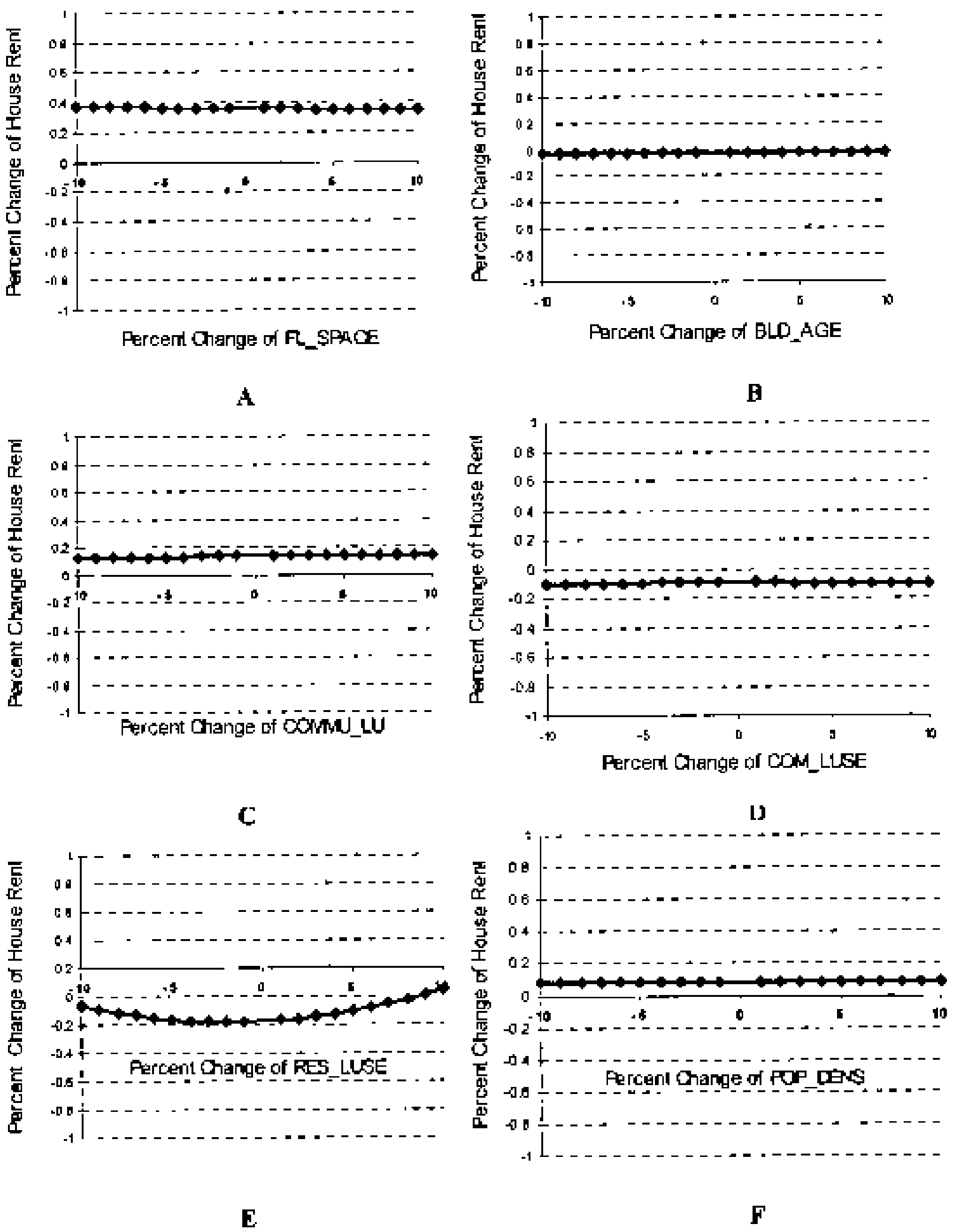
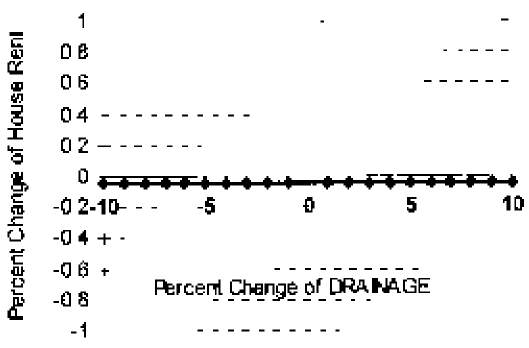
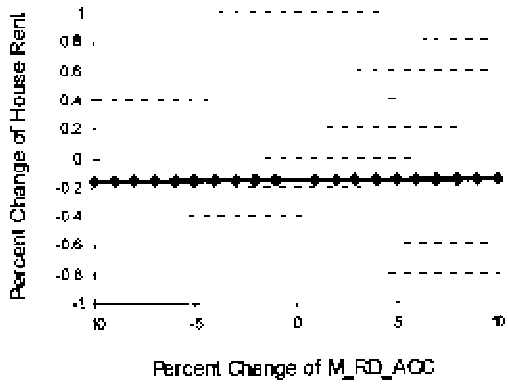


Figure 5.8: House rent elasticity with respect to different independent variables





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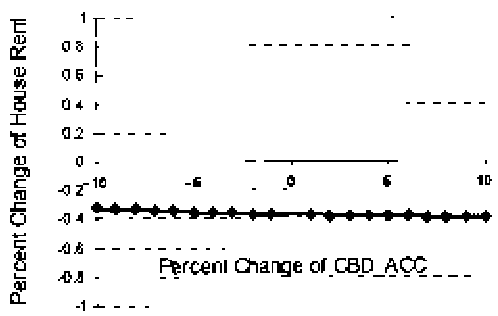

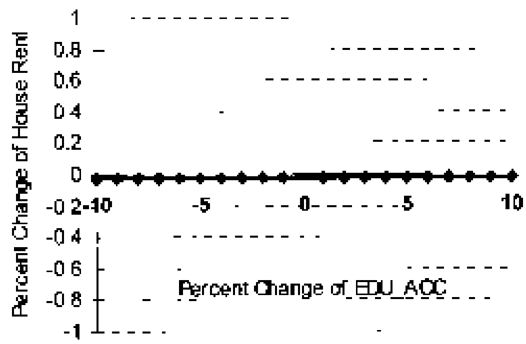

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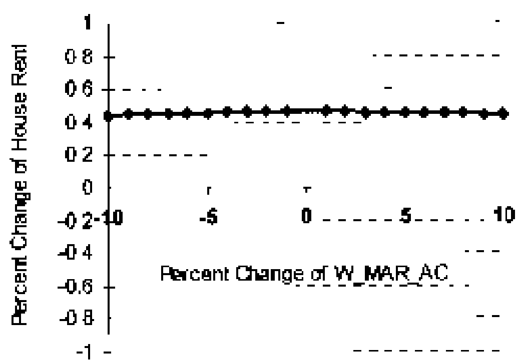

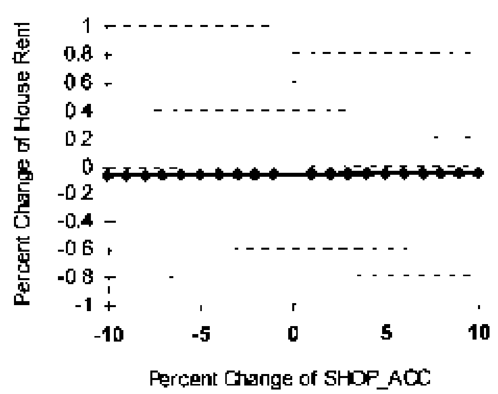

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Figure 5.8: House rent elasticity with respect to different independent variables

Fourteen independent variables had been used in this study to determine house rent. But for these analysis two independent variables namely number of bedrooms and number of bathrooms were not considered because they are discrete type variables. Elasticity of house rent was estimated with respect to the rest of the twelve independent variables using ANN model. The ANN model was first trained with 369 residential properties and then tested with a hypothetical cases consisting of average values of thirteen out of fourteen independent variables with the value of the remaining independent variable varying from 10% below average to 10% above average in 1% increment. Figure 5.8 shows the percent change of house rent at different points with respect to different independent variables.

Table 5.6: Summary of house rent elasticity estimation

Independent Variables	Percent Increase of Independent Variables from Average Value	Percent Change of House Rent
FL_SPACE	1%	0.35 %
BEDS	1%	0.29 %
BATHS	1%	0.24 %
BLD_AGE	1%	-0.03 %
POP_DENS	1%	0.09 %
RES_LUSE	1%	-0.17 %
COM_LUSE	1%	-0.10 %
COMMU_LU	1%	0.13 %
DRAINAGE	1%	-0.05 %
M_RD_ACC	1%	-0.16 %
CBD_ACC	1%	-0.37 %
W_MAR_AC	1%	0.46 %
EDU_ACC	1%	-0.03 %
SHOP_ACC	1%	-0.06 %

Table 5.6 shows the summary of house rent elasticity estimation. Table 5.6 illustrates that with 1% change of the value of different independent variables the house rent changes by -0.03% to 0.46%. The maximum 0.46% change of house rent occurred due to 1% change of the value of network access distance from property to wholesale markets. It is also found that an increase of network access distance from property to CBD by 1% will result in a decrease of house rent by 0.37%. On the other hand, house rent was changed by only 0.03% due to 1% value increase of BLD_AGE,

EDU_ACC. Since the changes of house rent due to the changes of independent variables are not very significant, it can be said that the developed ANN model is a robust model.

5.4 Summary

The developed ANN model was trained with 360 residential properties (training set) and their predictability in estimating value was tested with the remaining 119 residential properties (prodnction set). The neural network model built for this data set utilized fourteen independent variables. The initial ANN model created with 17 hidden neurons exhibited superiority with a R^2 value of 0.5967. The initial model had a mean absolute error of 24.6% and it predicted 13.45% residential property with average absolute error below 5%. On the other hand the best neural network model was developed utilizing ten independent variables with 80 hidden neurons. The R^2 value of the best model was 0.6210 with a mean absolute error of 22.52%. The relative contribution factor of the initial ANN model shows that network access distance from property to central business district (CBD_ACC), percentage of area dedicated to commercial use (COM_LUSE), percentage of area dedicated to residential use (RES_LUSE) are important factors that determine the residential property rent of Rajshahi City. In both models it is seen that land use plays a very important role in determining house rent in Rajshahi City. After elasticity estimation it is seen that with 1% change of the value of different independent variables the house rent changes by -0.03% to 0.46%. On the basis of the result of this developed model, the comparative analysis of the predictive power of ANN model and hedonic price model are presented in the following chapter.

Chapter 6

NEURAL NETWORK MODEL VS HEDONIC PRICE MODEL

Chapter 6: Neural Network Model Vs Hedonic Price Model

6.1 Introduction

One of the main objectives of this study is to compare the predictive performance of a neural network model and a hedonic price model in the context of house rent. This chapter presents the comparative analysis of both models. Three criteria were used for comparing the performance of the two models: (1) the mean absolute error between the predicted and actual house rent, (2) the percentage of houses in the sample whose absolute error was less than 5% of the actual rent and (3) the coefficient of determination R^2. The best model for predicting actual house rent was determined to be the one that resulted in the lowest mean absolute percentage error, higher R^2 and/or the highest percentage of predicted rent with absolute errors below 5% of the actual house rent. The comparison was conducted in six stages or cases. The first case conducted the predictive power comparisons utilizing the whole data set for training and testing. In the second case the models were trained with 360 houses and their predictability in estimating value were tested with remaining 119 houses. In the third case, the ANN model is compared with the best reduced hedonic price model and the fourth case classified the data set into three house rent range. The fifth case restricted the data set to include a more homogeneous set of houses from a single strategic planning zone area. Finally in the sixth case the tests were conducted both for a normal sample of properties as well as an outlier sample of properties. The best neural network models developed for all the cases were determined utilizing a sequential trial and error method. The best model was selected based upon the minimum mean absolute error prediction error and the maximum percentage of houses within a 5 per cent absolute prediction error of the actual house rent.

6.2 Case 1

The both models in this analysis,were trained with 479 houses and their predictability in estimating value was tested with the same number of houses. All of the models built for this case utilized all fourteen variables which were used to develop the initial neural network model. The hedonic price model was generated using the linear functional form specification. The coefficients and model summary are presented in Table 6.1. The coefficient of determination R^2 is 0.552.

Table 6.1: Coefficients and model summary of linear OLS hedonic model

Variables	Unstandardized Coefficients		Standardized Coefficients	t Distribution	Sig.
	B	Std. Error	Beta		
(Constant)	-908.143	540.210		-1.681	.093
FL_SPACE	.298	.038	.284	7.802	.000
BEDS	383.842	43.993	.367	8.725	.000
BATHS	163.865	60.967	.111	2.688	.007
BLD_AGE	-1.578	2.166	-.025	-.728	.467
POP_DENS	1.355	1.158	.057	1.171	.242
RES_LUSE	16.621	13.420	.105	1.238	.216
COM_LUSE	24.192	28.069	.076	.862	.389
COMMU_LU	87.126	54.703	.141	1.593	.112
DRAINAGE	-.257	.390	-.034	-.660	.509
M_RD_ACC	-.392	.079	-.227	-4.986	.000
CBD_ACC	.044	.129	.067	.344	.731
W_MAR_AC	.154	.133	.226	1.160	.247
EDU_ACC	-.026	.031	-.027	-.831	.406
SHOP_ACC	.000	.079	-.001	-.005	.996

Model Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
.743	.552	.539	612.448

a. Predictors: (Constant), SHOP_ACC, EDU_ACC, BATHS, BLD_AGE, FL_SPACE, POP_DENS, BEDS, M_RD_ACC, COM_LUSE, DRAINGE, RES_LUSE, COMMU_LUSE, CBD_ACC, W_MAR_AC

b. Dependent Variable: RENT

The generated neural network model for 479 houses is shown in Figure 6.1. The coefficient of determination R^2 of this ANN model is 0.7295.

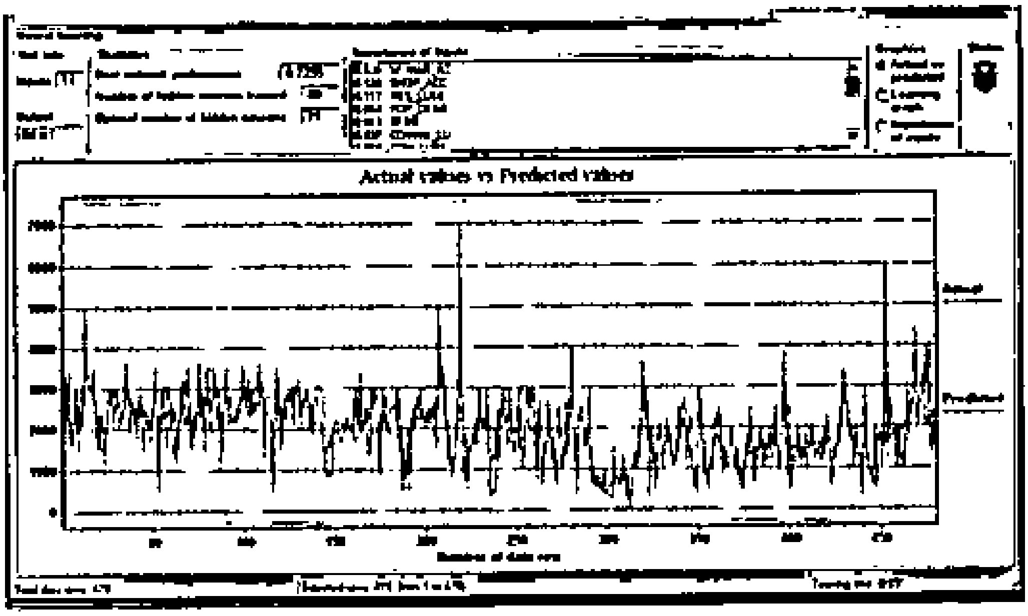


Figure 6.1: Neural Network model

Table 6.2 illustrates the prediction results of both models for case 1. From Table 5.7 it can be observed that the neural network model outperforms the hedonic price model in terms of all of the three criteria. The neural network model had a lower mean absolute error of 25.71% while hedonic price model had a mean absolute error of 29.97%. These findings indicate that in this case, the neural network models did outperform the hedonic price model.

Table 6.2: Prediction results of two models

Absolute Error Range (%)	Neural Network Model		Hedonic Price Model	
	%	No of Houses	%	No of Houses
0-5	17.33	83	14.61	70
0-10	33.40	160	27.56	132
0-20	59.29	284	45.09	216
>20	40.71	195	54.91	263
Mean Absolute Error	25.71	123	29.97	143
R^2	0.7295		0.552	

In terms of the percentage of predicted house rent within 5% of the actual rent, the neural network model also gave better result than hedonic price model. As detailed in Table 6.2, the neural network model predicted a higher number of houses with an absolute error below 5 % (17.33%) while hedonic price model predicted 14.61% of the houses within the 5% absolute error range. As the absolute error range is increased, neural network model outperforms the hedonic price model for the 0-10% range and the 0-20% range and the greater than 20% range of error. These results had the similarity with the Do and Grudnitski 1992) results which found that their neural network model had higher number of properties with less than 5% error than their hedonic price model.

The coefficient of determination R^2 value of neural network model (0.7295) is significantly higher than the R^2 value of hedonic price model (0.552). The results imply that the neural network model can estimate the house rent more accurately than the hedonic price model.

6.2.1 Relative contribution of inputs for both models

In the case of neural network model the relative contribution factor in Table 5.8 shows that network access distance from property to wholesale markets (W_MAR_AC) is the most important factor in determining the house rent where as in hedonic price model the number of bedrooms of the residential properties (BEDS) is the most influential predictor with a coefficient of 0.367(Table 6.1). In neural network model, network access distance from property to shopping centers (SHOP_ACC), another transportation attribute, is ranked second in terms of contribution (0.122) followed by a neighborhood attribute, RES_LUSE (0.117). On the other hand, usable living area is ranked second in terms of contribution (0.284) in hedonic price model which is followed by a transportation attribute W_MAR_AC. So W_MAR_AC was found important in both the models.

Table 6.3: Relative contribution of inputs in ANN model

Variable	Relative Importance value
W_MAR_AC	0.53
SHOP_ACC	0.122
RES_LUSE	0.117
POP_DENS	0.064
BEDS	0.043
COMMU_LU	0.037
COM_LUSE	0.018
CBD_ACC	0.015
DRAINAGE	0.015
EDU_ACC	0.013
BATHS	0.01
M_RD_ACC	0.009
FL_SPACE	0.004
BLD_AGE	0.003

6.3 Case 2

The models in this analysis were trained with 360 houses and their predictability in estimating value was tested with the remaining 119 houses. The predictive model built for this case utilized the same fourteen independent variables. The results for case 2 are close between the neural network model and the hedonic price model. Figure 6.2 shows the actual and predicted rent of 119 houses of both models. From the figure it is seen that the neural network model can predict more accurately than the hedonic price model. Table 6.4 illustrates that the neural network model had a higher R^2 value of 59.67% than the hedonic price model (52.91%). This indicates that in this case neural network can predict the house rent more accurately than the hedonic price model. The neural network model had a mean absolute error of 24.61% while hedonic price model had a mean absolute error of 26.70%. So in terms of mean absolute error neural network model did outperform the hedonic price model but only marginally. This result is contrary to the findings of the Do and Grudnitski (1992) study that reported the neural network mean absolute error (6.9%) to be significantly smaller than that of regression (11.3%), but supports the results of Worzala *et al.* (1995) study that reported the neural network mean absolute error (14.4%) to be marginally higher than the their regression results (15.2%).

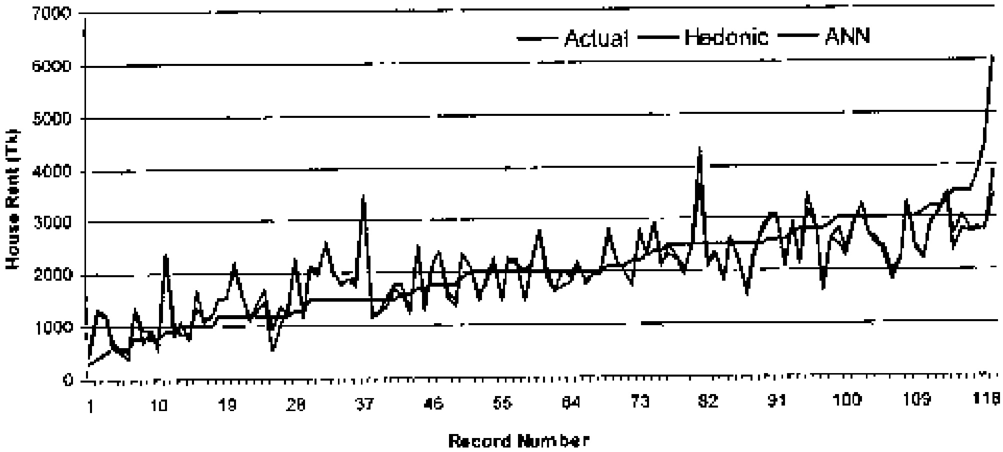


Figure 6.2: Actual and predicted house rent of 119 test sample

As detailed in Table 6.4, both the neural network model and the regression model predicted the same number of houses with an absolute error below 5 % (13.45%). Worzala *et al.* (1995) reported the same result where both the models predicted the same number of houses with an absolute error below 5 % (32.4%). However, as the absolute error range is increased, the neural network model becomes the better overall predictor for the 0-10% range, the 0-20% range and the greater-than-20% range of error.

Table 6.4: Prediction Results of Two Models Using Case 2 Data

Absolute Error Range (%)	Neural Network Model		Hedonic Price Model	
	%	No of Houses	%	No of Houses
0-5	13.45	16	13.45	16
0-10	26.05	31	24.37	29
0-20	57.14	68	52.10	62
>20	42.86	51	47.90	57
Mean Absolute Error	24.61	29	26.70	32
R^2	0.5967		0.5291	

Table 6.5 presents the results segmented by rent ranges of the test sample. At the lowest rent range, ANN was the better performer in terms of the mean absolute error test (38.5%). ANN model had twice the percentage of properties (14.6%) with less than 5% error than the hedonic model (7.3%). In rent range of Tk. 1501- 2500, the neural network model does the best job. The neural network model slightly outperformed the hedonic price model in the mean absolute error test (16% compared to 16.1%) and it also did a better job of predicting rent within 5% of the actual rent (22.9%) than the hedonic model (8.7%) in this rent range. In the highest rent range (Tk. 2500+), ANN again does a better job in predicting the actual rent than hedonic model in terms of mean absolute error test and the 5% error test.

Table 6.5: Comparison of the predictive power of each model per price range using Case 2 data

Rent Range	No of Houses	ANN		Hedonic Price Model	
		Mean Absolute Error (%)	Error Below 5% (%)	Mean Absolute Error (%)	Error Below 5% (%)
Tk. 0 - 1500	41	38.5	14.6	43.3	7.3
Tk. 1501 - 2500	48	16.0	22.9	16.1	18.7
Tk. 2501+	30	17.8	16.7	19.3	13.3

6.4 Case 3

In this case the best reduced hedonic price model for residential property rent asking price developed by Habib (2004) was compared with the neural network model. The neural network model was developed utilizing those independent variables which were finally selected for best reduced hedonic price model. There are several methods of regression for best reduced model depending on the method of entry and removal of independent variables to and from the regression model. This study used the stepwise method to find out the best-reduced model which was used by Habib (2004) in order to enhance the comparability of results between the two studies.

In total, six models had been constructed in the stepwise regression procedure. To insure replication of the methodology utilized by Habib (2004), two criteria had been used in removing independent variables in the stepwise regression method. They were based on an F statistic that is the square of the t statistic. The first criterion for removing variables was the minimum F value that a variable must have to remain in the model. This minimum value is sometimes known as the *F-to-enter*. The second criterion is the maximum probability of *F-to-remove*. In this study, the second criterion was used with a value of 0.10 for the maximum probability of *F-to-remove* and 0.05 was selected for the minimum probability of *F-to-enter* in the regression models. The model summary found after running stepwise regression is presented in Table 6.6.

Table 6.6: Model Summary

Model	R^2	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.620	.385	.384	708.054
2	0.679	.461	.459	663.436
3	0.711	.506	.503	635.762
4	0.723	.523	.519	625.731
5	0.731	.534	.529	618.942
6	0.737	,543	.538	613.201

1. Predictors: (Constant), BEDS

2. Predictors: (Constant), BEDS, FL_SPACE

3. Predictors: (Constant), BEDS, FL_SPACE, COMMU_LU

4. Predictors: (Constant), BEDS, FL_SPACE, COMMU_LU, M_RD_ACC

5. Predictors: (Constant), BEDS, FL_SPACE, COMMU_LU, M_RD_ACC, W_MAR_AC

6. Predictors: (Constant), BEDS, FL_SPACE, COMMU_LU, M_RD_ACC, W_MAR_AC, BATHS

* Dependent Variable: Rent

Among the six models, the best reduced model is comprised of three structural attributes (BEDS, FL_SPAC and BATHS), one neighborhood attribute name (COMMU_LU) and finally two transportation attributes (M_RD_ACC, W_MAR_AC) with a coefficient of determination R^2 of 0.543.

For this case the neural network model was developed utilizing the above six independent variables which were finally selected for the best reduced hedonic price model. The final model result found utilizing these six variables is shown in Fignre 6.3. From figure it can be seen that the coefficient of determination R^2 value of the model was 0.6153.

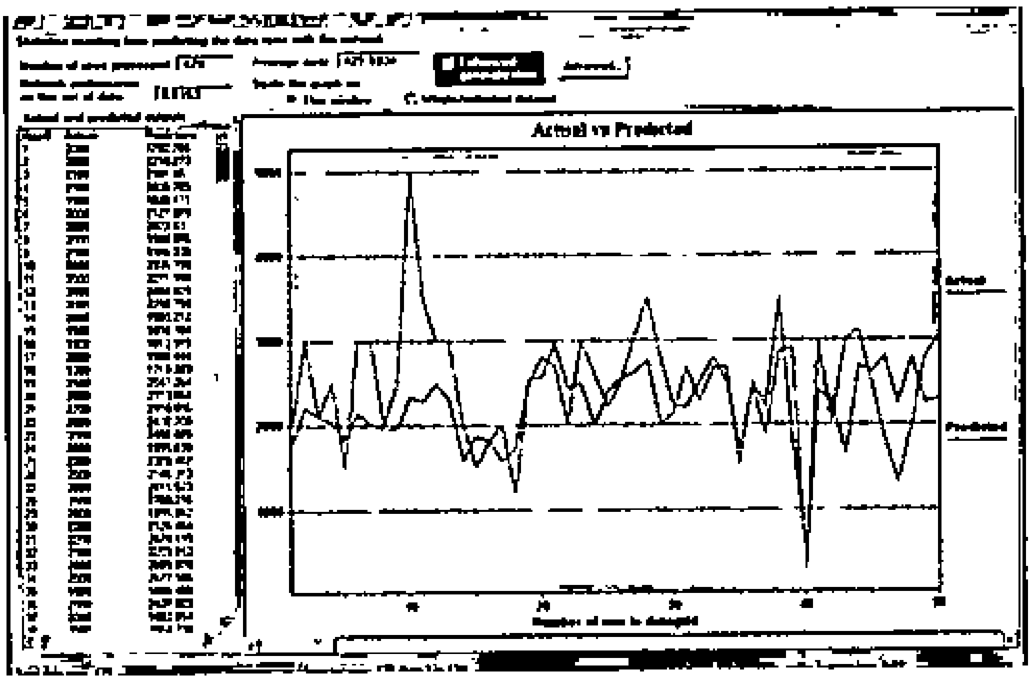


Figure 6.3: ANN model using case 3 data

Table 6.7: Predicting Results of Two Models Using Case 3 Data

Absolute Error Range (%)	Neural Network Model		Hedonic Price Model	
	%	No of Houses	%	No of Houses
0-5	15.87	76	14.61	70
0-10	29.44	141	28.18	135
0-20	55.95	268	52.19	250
>20	44.05	211	47.81	229
Mean Absolute Error	28.22	135	30.14	144
R^2	0.6153		0.543	

Table 6.7 presents the results of best reduced hedonic price model and neural network model. These results further evidence that consistency exists in the neural network models' better ability to accurately predict the actual house rent over the hedonic price model. The neural network model performed better in terms of the mean absolute error test (28.22% compared to 30.14%). The neural network model did a better job of predicting house rent within 5% of the actual rent (15.87%) than the hedonic price model (14.61%). The neural network model outperforms the hedonic price model as the absolute error range is increased. Since the R^2 value from

neural network model (61.53%) is higher than the hedonic price model (54.3%), it can be said that the neural network model can estimate the house rent more accurately than the hedonic price model.

6.5 Case 4

The data used in this case were classified into three house rent ranges. The ranges are Tk. 0 to 1500, Tk. 1501 to 2500 and more than Tk. 2500. In this analysis the models of each rent range were trained with one data set and tested with other data set. All of the predictive models built for this case utilized the same fourteen independent variables. The sample number of houses representing each data set is given in Table 6.8. The two samples of each price range were created by first sorting the houses by location, then by rent, and then by picking every fourth house for the production set. Table 6.9, 6.10 and 6.11 detail the descriptive statistics of the entire sample of each rent range and two subsets for training and testing. As can be seen from the tables, there were no significant differences between the training and testing data subsets of each rent range and each is a fair representation of the entire data set.

Table 6.8: Training and test sample size of each rent range

Rent Range	Training Sample (No of houses)	Test Sample (No of houses)	Total (No of houses)
Tk. 0 - 1500	135	45	180
Tk. 1501- 2500	138	46	184
Tk. 2500+	87	28	115

Table 6.9: Descriptive Statistics of Sample house for rent range 0-Tk.1500

Variables	Mean			Maximum			Minimum		
	Entire Sample	Training Set	Testing Set	Entire Sample	Training Set	Testing Set	Entire Sample	Training Set	Testing Set
RENT	1043.6	1043.6	1043.6	1043.6	1043.6	1043.6	1043.6	1043.6	1043.6
FL_SPACE	1079.5	1053.1	1158.9	6000.0	4000.0	6000.0	200.0	200.0	300.0
BEDS	2.0	1.9	2.2	4 0	4.0	4.0	1.0	1.0	1.0
BATHS	1.1	1.1	1.2	2.0	2.0	2.0	0.0	0.0	0.0
BLD_AGE	16 2	15.9	16.9	69.0	59.0	69.0	2 0	2 0	2 0
POP_DENS	54.2	54.0	55.0	161.7	161.7	161.7	7.4	7.4	7 4
RES_LUSE	38 6	38 7	38.6	45.4	45.4	45.4	27 0	27 0	27.0
COM_LUSE	4 5	4.5	4.4	8.6	8.6	8 6	1 4	1 4	1.4
COMMU_LU	2.4	2.4	2 4	5.3	5.3	5.3	0.2	0.2	0 2
DRAINAGE	114.0	112.5	118.4	760.1	611 0	760.1	2.5	2.5	3.1
M_RD_ACC	1135.6	1138.5	1126.6	2871.5	2871.5	2627.1	175.0	175.0	305.0
CBD_ACC	2939 3	2950.1	2907.1	5603.6	5603.6	5499 9	320.3	381.6	320 3
W_MAR_AC	2497.2	2503.6	2477.9	5603.4	5603.4	5359.1	183 4	183.4	320.5
EDU_ACC	892.2	904 6	855.0	2703.8	2703.8	2369.3	3.1	3.1	35.3
SHOP_ACC	2340 3	2341 1	2337.8	5691.1	5691.1	5446 7	149.6	219.9	149.6

Table 6.10: Descriptive Statistics of Sample house for rent range of Tk. 1501-2500

Variables	Mean			Maximum			Minimum		
	Entire Sample	Training Set	Testing Set	Entire Sample	Training Set	Testing Set	Entire Sample	Training Set	Testing Set
RENT	2143 1	2142.2	2145.7	2500.0	2500.0	2500.0	1580.0	1580.0	1600.0
FL_SPACE	1614.7	1630.6	1567 2	8000.0	8000.0	2600.0	500.0	500.0	600 0
BEDS	2.9	3 0	2.7	4.0	4 0	4.0	2.0	2.0	2.0
BATHS	1.6	1.6	1.6	3.0	3.0	3.0	1 0	1.0	1.0
BLD_AGE	20.1	21.3	16.5	129 0	129.0	51.0	2.0	2 0	2.0
POP_DENS	68.9	69.2	67.9	161.7	161.7	161 7	7 4	7.4	7 4
RES_LUSE	42.2	42.3	42.0	45 4	45.4	45.4	27.0	27.0	27.0
COM_LUSE	6 5	6.5	6.5	8 6	8.6	8.6	1.4	1.4	1.4
COMMU_LU	3.3	3.3	3 3	5.3	5.3	5.3	0.2	0.2	0.2
DRAINAGE	33 9	32.1	39.3	733.9	403.5	733.9	1 3	1.3	3 4
M_RD_ACC	855.5	854.1	859 4	2246.0	2054.7	2246.0	188.2	207.3	188.2
CBD_ACC	2021.0	2018.9	2027.2	5404.6	5404.6	4946 1	207.5	207 5	349.2
W_MAR_AC	1656.9	1648.3	1682.6	4945.9	4842.3	4945 9	207.3	207 3	239.9
EDU_ACC	936.3	997.2	753.6	17775.6	17775.6	2305.8	7.9	7.9	65 9
SHOP_ACC	1554.7	1545.6	1582.1	5084.5	5084.5	5033.5	114 6	114.6	223.3

Table 6.11: Descriptive Statistics of Sample house for rent range of more than Tk. 2500

Variables	Mean			Maximum			Minimum		
	Entire Sample	Training Set	Testing Set	Entire Sample	Training Set	Testing Set	Entire Sample	Training Set	Testing Set
RENT	3109.1	3109.1	3100.0	7000.0	7000.0	6000.0	2600.0	2600.0	2600.0
FL_SPACE	2107.7	2107.7	2024.6	7000.0	7000.0	4320.0	800.0	800.0	1000.0
BEDS	3.2	3.2	3.2	4.0	4.0	4.0	1.0	1.0	2.0
BATHS	1.9	1.9	2.0	3.0	3.0	3.0	1.0	1.0	1.0
BLD_AGE	20.0	20.0	20.6	69.0	69.0	52.0	1.0	1.0	2.0
POP_DENS	74.1	74.1	72.5	161.7	161.7	111.5	9.5	9.5	9.5
RES_LUSE	43.5	43.5	43.5	45.4	45.4	45.4	28.4	28.4	28.4
COM_LUSE	7.4	7.4	7.3	8.6	8.6	8.6	1.8	1.8	1.8
COMMU_LU	3.9	3.9	3.8	5.3	5.3	5.3	1.0	1.0	1.0
DRAINAGE	28.5	28.5	20.4	702.2	702.2	171.2	2.5	2.5	4.7
M_RD_ACC	685.8	685.8	620.1	2341.1	2341.1	1429.0	48.8	48.8	48.8
CBD_ACC	1755.3	1755.3	1691.9	5041.2	5041.2	3652.7	225.2	225.2	225.2
W_MAR_AC	1466.7	1466.7	1381.9	5041.0	5041.0	3521.6	82.1	82.1	121.9
EDU_ACC	934.6	934.6	897.3	2475.0	2475.0	2475.0	21.7	21.7	21.7
SHOP_ACC	1226.3	1226.3	1142.3	5128.6	5128.6	3740.1	88.3	88.3	88.3

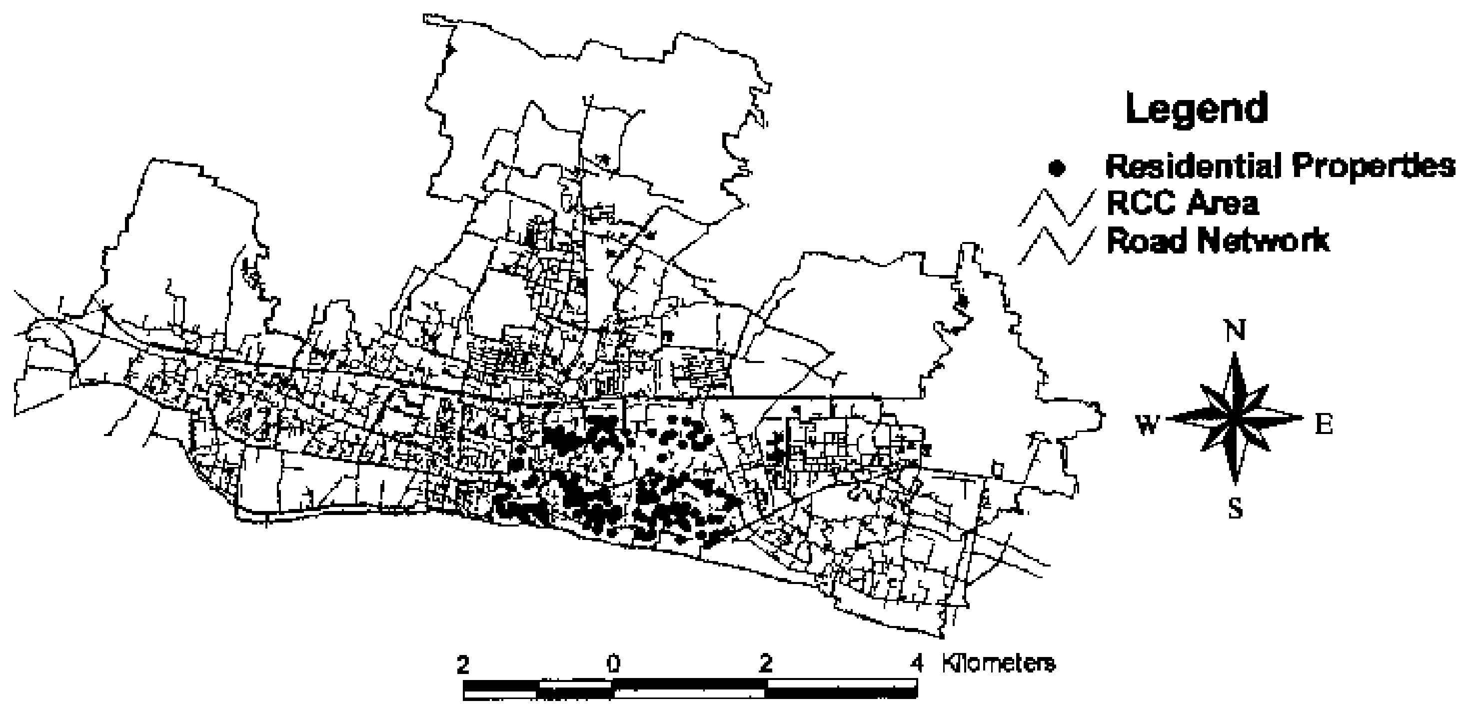
Table 6.12 shows the prediction results of each model for different house rent range. It can be seen from table that when the data set was constrained to different house rent ranges, the results for mean absolute error of ANN models for each rent range was less than that of hedonic price models. The neural network models predicted the higher percentage of houses than the hedonic model with an absolute error below 5% for all the rent range. So in terms of the percentage of predicted rent with 5% of the actual rent, the neural network models outperformed the hedonic models. The maximum absolute error showed that the neural network model became better model than the hedonic price model since the neural network model had lower maximum absolute errors for all three rent ranges. Therefore, the results provide a clear evidence of neural network model's superiority over the hedonic price model in predicting house rent.

Table 6.12: Prediction result of each model using Case 4 data

Rent Range	ANN			Hedonic		
	Mean Absolute Error (%)	Maximum Absolute Error (%)	Error Below 5% (%)	Mean Absolute Error (%)	Maximum Absolute Error (%)	Error Below 5% (%)
Tk. 0 - 1500	27.93	156.51	20	28.13	157.48	20
Tk. 1501 - 2500	8.37	20.81	39.13	9.39	44.47	36.96
Tk. 2500+	8.33	39.009	42.86	8.94	44.89	39.29

6.6 Case 5

The data in case 5 was constrained to a more homogeneous set of houses. This was accomplished by including houses from only one Strategic Planning Zone (SPZ) area defined by the Rajshahi Master Plan Project. The models were trained with 145 houses and tested with 48 houses, representing a homogeneous set of houses from SPZ no. 18 area. The location of these houses is shown in Map 6.1. The two samples were created by first sorting the houses by rent and then by picking every fourth house. The models built for this case utilized the following eleven independent variables: usable living area, number of bedrooms, number of bathrooms, age of residential property structure, population density, Euclidian distance from the property to nearest point of drainage network, network access distance from property to central business district (CBD), network access distance from property to wholesale markets, network access distance from property to primary school, network access distance from property to shopping centers. Three variables namely percentage of area dedicated to residential use, percentage of area dedicated to commercial use, percentage of area dedicated to community facilities have been removed from models because there are same values of these three variables in all of the data set. Table 6.13 contains the descriptive statistics for this case.



Map 6.1: Location of Residential Properties Using for Case 5 Data

6.13: Descriptive Statistics of Sample houses for Case 5: SPZ no 18

Variables	Mean			Maximum			Minimum		
	Entire Sample (193)	Training Set (145)	Testing Set (48)	Entire Sample	Training Set	Testing Set	Entire Sample	Training Set	Testing Set
RENT	2145.8	2134.8	2178.8	5000.0	5000.0	5000.0	350.0	350.0	500.0
FL_SPACE	1581.6	1594.4	1543.0	8000.0	8000.0	2800.0	200.0	200.0	200.0
BEDS	2.9	2.9	2.9	4.0	4.0	4.0	1.0	1.0	2.0
BATHS	1.6	1.6	1.7	3.0	3.0	3.0	1.0	1.0	1.0
BLD_AGE	22.3	22.2	22.6	129.0	102.0	129.0	1.0	2.0	1.0
POP_DENS	90.2	89.2	93.2	161.7	161.7	161.7	35.8	35.8	35.8
DRAINAGE	20.3	20.7	19.4	281.1	281.1	133.0	1.3	1.3	3.3
M_RD_ACC	805.6	811.4	788.2	2200.4	2200.4	1519.6	206.9	206.9	278.7
CBD_ACC	1497.4	1494.4	1506.4	5142.8	5142.8	3012.9	207.5	207.5	320.3
W_MAR_AC	1212.6	1215.8	1202.8	4988.0	4988.0	2613.9	176.5	183.4	176.5
EDU_ACC	709.5	693.5	757.9	2583.8	2583.8	1627.6	21.7	21.7	43.6
SHOP_ACC	1377.2	1365.5	1412.6	5230.2	5230.2	3025.7	114.6	149.6	114.6

The results of the neural network model, in terms of the mean absolute error, were better than the results with Case 2 data but worse for the hedonic price model. In terms of mean absolute error, neural network model (24.3%) outperformed the hedonic model (27.3) in this case.

6.14: Prediction results for both models using Case 5 data.

Absolute Error Range (%)	Neural Network Model		Hedonic Price Model	
	%	No of Houses	%	No of Houses
0-5	18.8	9	16.7	8
0-10	25.0	12	25.0	12
0-20	54.2	26	47.9	23
>20	45.8	22	52.1	25
Mean Absolute Error	24.3	11	27.3	13
R^2	0.512		0.501	

Table 6.14 shows the percentage of houses that had predicted values within 5% of the actual rent increased for both models in the current case. The neural network model had a higher percentage (18.8% compared to 16.7%). Both models gave the same result at the 0-10% range whereas the ANN model had fewer houses in the 0-20% error range and greater than 20% error range. Figure 6.4 shows the actual and predicted rent of both models for case 5 data. From the figure it is seen that the neural network model can predict more accurately than the hedonic price model. In this case, the R^2 from the neural network model (0.512) is slightly higher than the R^2 of the hedonic price model (0.501). These results indicate that with a homogenous set of data neural network model had better prediction capability of house rent than the hedonic price model.

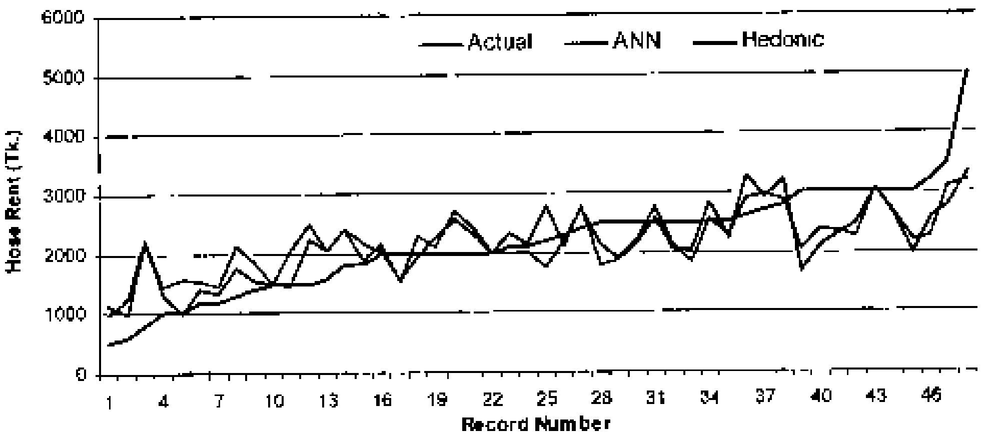


Figure 6.4: Actual and predicted house rent of two models using Case 5 data

6.7 Case 6

The case compares the predictive performance of ANN model and hedonic price model with respect to their ability to estimate the value of a random sample of "normal" residential properties and a sample of outlier properties. Outlier properties were determined as properties that possessed a z-score greater than 1.7. A z-score was measured by subtracting the property rent from the average rent of the houses in the sample and dividing by the sample standard deviation. Thirty outlier properties were identified and separated into an "outlier" holdout sample, leaving 449 properties in the "normal properties" data set. The remaining 449 properties were sorted by rent and every fourth property was separated out into a "normal" holdout sample, leaving 337 properties to be the training sample for creating both the ANN model and hedonic price model. Table 6.15 details the descriptive statistics for each of these data subsets. There were no significant differences between the training and the normal holdout data sets. The average house rent in both the training set and normal holdout sample was approximately Tk. 1900, and standard deviation of Tk. 752 was observed. House rents in these two subsets ranged from Tk. 500 to Tk. 3,300.

The properties in the outlier holdout sample exhibit significant differences from the training and normal samples. These properties were generally more expensive with an average rent of Tk. 2,500, a range of Tk. 300 to Tk. 7,000, and a standard deviation of Tk. 2,081. Fourteen variables, which have been used in the previous cases, were chosen as the independent variables for both models.

Table 6.15 Descriptive Statistics of Sample houses for Case 6

Varlables	Mean			Maximum			Minimum		
	Training Set (337)	Normal Set (112)	Outlier Set (30)	Training Set	Normal Set	Outlier Set	Training Set	Normal Set	Outlier Set
RENT	1922.7	1929.7	2521.7	3300.0	3200.0	7000.0	500.0	500.0	300.0
FL_SPACE	1551.5	1448.8	1622.7	8000.0	4400.0	4800.0	200.0	300.0	200.0
BEDS	2.6	2.7	2.6	4.0	4.0	4.0	1.0	1.0	1.0
BATHS	1.5	1.4	1.6	3.0	3.0	3.0	1.0	1.0	0.0
BLD_AGE	19.2	17.6	15.7	129.0	102.0	69.0	2.0	2.0	1.0
POP_DENS	65.1	65.3	56.7	161.7	161.7	161.7	7.4	7.4	9.5
RES_LUSE	41.3	41.5	38.9	45.4	45.4	45.4	27.0	27.0	28.4
COM_LUSE	5.9	6.1	5.5	8.6	8.6	8.6	1.4	1.4	1.8
COMMU_LU	3.1	3.1	2.8	5 3	5.3	5.3	0.2	0.2	1.0
DRAINAGE	62.6	52.7	101.1	760.1	611.0	391.4	1.3	2.3	2.6
M_RD_ACC	911 1	914.4	1040.5	2717 9	2627.1	2871 5	146.5	48.8	278.7
CBD_ACC	2276.1	2207.9	2949.8	5535.5	5376.2	5603 6	225.2	207.5	278.8
W_MAR_AC	1896.7	1834 3	2613.4	5449.9	5359.1	5603.4	82.1	173.6	278.9
EDU_ACC	938.4	896.4	790.5	17775.6	2475.0	2703.8	7.9	3 1	21.9
SHOP_ACC	1727.3	1717.1	2464.5	5537.5	5446 7	5691.1	149.6	88.3	366.6

Table 6.16 details the mean absolute error and maximum absolute error test results and the R2 value. ANN model performed better in normal hold out sample results. When measured by the mean absolute error test, the ANN model outperformed the hedonic price model. The maximum absolute error test showed that ANN model did outperform the hedonic price model (317.9 per cent vs. 320.7 per cent). The higher R2 value of ANN model (0.612 compared to 0.564) indicates that the ANN model can predict the house rent more accurately than the hedonic price model. Thus, the results indicate the out performance of ANN model for the normal holdout sample.

The results from the outlier sample clearly demonstrate the lower performance of hedonic price model in comparison to ANN model. ANN model had the mean absolute error of 78.1% which is far better than that of hedonic price model (104.3%). The maximum absolute error test showed the better performance of ANN model (300.3 per cent compared to 338.8 per cent). ANN model can predict the outlier properties more precisely than the hedonic price model since its R^2 value is significantly higher than the hedonic price model (0.579 vs. 0.478). So the results show that ANN model outperformed the hedonic price model for the outlier holdout sample.

Table 6.16: Prediction results for both models using Case 6 data

	Results of the "Normal" Holdout Sample		Results of the "Outlier" Holdout Sample	
	ANN	Hedonic Pricing	ANN	Hedonic Pricing
R^2	0 612	0.564	0.579	0.478
Mean Absolute Error (%)	24.3	26.7	78.1	104.3
Maximum absolute Error (%)	317.9	320.7	300.3	338.8

Table 6.17 shows the percentage of predicted value within 0-5 per cent, 0-10 percent, 0-20 percent and over 20 percent absolute error from the actual house rent. The results for the normal holdout sample show that ANN model had twice the percentage of houses with less than 5% error than their hedonic price model which coincides with the Do and Grudnitski (1992) results and with the increase of error range ANN model did outperform the hedonic price model.

Table 6.17: Predictive power of the models

Absolute Error Range (%)	Results of the "Normal" Holdout Sample		Results of the "Outlier" Holdout Sample	
	ANN (%)	Hedonic Pricing (%)	ANN (%)	Hedonic Pricing (%)
0-5	20.5	10.7	6.7	0.0
0-10	33.9	26.8	6.7	0.0
0-20	59.8	56.3	13.3	3.3
>20	40.2	43.8	86.7	96.7

The results from the outlier properties sample tests support the contention that hedonic price model are ineffective estimators of outlier values. Hedonic price model could not estimate any property within 5 per cent and 10 per cent of their actual rent where as ANN model predicated 6.7 per cent of houses for both the range. ANN model also outperformed the hedonic price model at the 0-20% arrange and the greater than 20% range of error. Therefore, the results provide clear evidence of superiority of ANN model for the outlier holdout sample.

6.8 Summary

The results discussed in this chapter indicate that the neural network model outperformed the hedonic price model in all of the cases in predicting house rent of Rajshahi City, although the difference between the two models was not large in all cases. Major concerns regarding the consistency of neural networks have been aired in the literature. The study found no problem of consistency. The analysis done with the neural network model gave better results consistently in all of the cases discussed. ANN model as well as hedonic price model performed better when they were trained and tested with same data set and they performed poorly when they were used for out-of-sample forecast, although in both cases ANN models outperformed the hedonic price models. ANN model also showed its supremacy in predicting outlier data set. As a result, the ANN model yields better prediction results compared to the hedonic price model. Based on the analysis of this chapter some recommendations have been formulated in the following chapter including concluding remarks.

Chapter 7

CONCLUSION AND RECOMMENDATION

Chapter 7: Conclusion and Recommendation

7.1 Conclusion

The study has developed an artificial neural network model for house rent prediction using 479 house information of Rajshahi City. The R^2 of the developed ANN model is 0.621 for sample forecast. The study has demonstrated that neighborhood attributes are the most significant factors in determining the house rent of Rajshahi City. The percentage of area dedicated to community facilities and percentage of area dedicated to commercial use have contributed more to the predictive power of model than the other attributes. So it is seen that land use has a great impact on house rent in Rajshahi City.

The study also empirically compares the predictive power of the artificial neural network model with the hedonic price model on house rent prediction. The comparison was conducted in six stages or cases. The first case conducted the predictive power comparisons utilizing the whole data set for training and testing. In the second case the models were trained with 360 houses and their predictability in estimating value were tested with remaining 119 houses. In the third case, the ANN model is compared with the best reduced hedonic price model and the fourth case classified the data set into three house rent range. The fifth case restricted the data set to include a more homogeneous set of houses from a single strategic planning zone area. Finally in the sixth case the tests were conducted both for a normal sample of properties as well as an outlier sample of properties. The results indicate that the neural network model outperformed the hedonic price model in all of the cases. In this study, the ANN model consistently gave better result than the hedonic price model, although the difference between the two models was not too large. ANN model and hedonic price model both do better when they are trained and tested with the same data set but they performed poorer on out-of -sample forecast. But in both cases ANN model showed better results in comparison to hedonic price model. The study also supports the superiority of ANN model in prediction of outlier holdout sample. The artificial neural network model can overcome some of the problems related to the data patterns and the underlining assumption of the hedonic price model. As a result the model can give a better prediction result when compares with the hedonic price model. Nevertheless, it should be noted that the optimal artificial neural network model is created by a trial and error strategy. Without this strategy the results may not indicate superiority of the neural network model.

The study indicates that some problems are encountered during the development and implementation of the ANN model. The problems are that the proper settings for the models are not obvious and it takes several iterations to find the set of parameters that best fit an application. Like some other studies (Worzala et al. 1995; Allen and Zumwalt, 1994), this study found that small changes can result in very different findings and the stopping point of learning is critical. In some cases it is very difficult to prevent overtraining.

In light of the short comings of the hedonic price model and the comparative goodness of the results of the neural network, the study supports the conclusion of Do and Grudnitski (1992) who indicated that a neural network model performs better than a multiple regression model for estimating the value of residential property.

7.2 Recommendations

While the results of this stndy indicate that neural networks are very reliable, it is also necessary to do further research on larger and different data set to establish the superiority of ANN model over the hedonic price model. More research conld determine if other software package and/or other data sets experience similar results. For example the current results might not be representative of all possible data sets and further research would determine the sensitivity of the valuation technique to data differences. It may be possible that neural networks will do much better job than hedonic price model if the nonlinear relationships between the variables are greater. This study considered only one year rent information of the houses. The time effect of the house rent, which could potentially impact the estimated results was ignored in this study (the same house should have different rent in different years, assuming the age factor is constant). So this time effect of the house rent should be considered in future research.

The results of this study do provide a practical recommendations regarding application of this model that if an artificial neural network model is to be used, the process and results of this study support a trial-and-error strategy to find the optimal artificial neural network model. It was only through this strategy that the neural network models created in this study could compete with the hedonic price models.

Finally cautions must be undertaken before any decision to utilize these methods in valuation practice of other urban areas. Because the results found in this study could be a function of the specific data characteristics of the sample used. However, despite the comparative advantage of ANN model in house rent prediction over traditional hedonic price model, the ultimate benefits of a neural network model can be fully realized when it performs better on larger and different data set.

Based on the findings of the study certain recommendations can be made for practical applications of this model in Bangladesh. Some recommendations may be also useful for plan formulation and implementations in Rajshahi City.

The Rajshahi Development Authority (RDA) should take low income housing projects apart from the central business district as the study showed that housing rents decrease with the increase of distance from the CBD at Rajshahi City. This study showed that the percentage of area dedicated to community facilities and percentage of area dedicated to commercial use had a great contribution in determination of house rent of Rajshahi City. So the Rajshahi Development Authority should develop housing projects in the areas where percentage of community facilities and commercial use is lower. The findings and developed model of this study is expected to be very helpful to the Rajshahi Development Authority (RDA) as they have already taken an extensive effort for transportation infrastructure investment to increment transportation network through the Rajshahi

Mater Plan Project. They can use this model to predict the house rent changes due to the implementation of this transportation project. By predicting house rent they can collect additional taxes/revenues for the implementation of the project in Rajshahi City.

An accurate prediction of house rent/price is important to real estate developers. Real estate business is now booming in urban areas of Bangladesh. The ANN model can be an effective tool for these developers and investors for estimating house rent/price more accurately over traditional methods. By using this model and results of this study the real estate developers can easily select location of different housing projects in Rajshahi City.

Public authorities can assess holding tax, regulate rent more easily using this model. Most of the house owners in Bangladesh built their houses by taking loan from Bank. This loan approval process is very time consuming due to the unavailability of any authentic property valuation techniques. The loan providers can use this model to estimate the house price which will help them to take decision whether they provide loan or not as well as regarding the amount of loan.

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APPENDIX A

Appendix A

Table: Structural Attributes and Coordinate locations of the residential properties

BUET_ID	FL_SPACE	BEDS	BATHS	BLD_AGE	X_COORD	Y_COORD
1	1400	2	1	8	360562.67420	695150.96325
2	1600	3	2	24	360445.78300	695183.70890
3	1700	3	1	24	360279.90030	695241.39260
4	1600	3	2	14	359869.68300	695307.41200
5	1400	3	1	25	359358.50600	695248.77990
6	1600	3	1	14	359510 66500	695604.10450
7	1600	3	1	14	359426.55350	695702.93000
8	1200	3	1	24	359596.96600	695777.31439
9	1400	3	1	9	359901.48400	695785.59350
10	1200	3	1	14	360075 61350	695744.52250
11	1400	3	1	19	360148.05100	695941.33850
12	2000	3	1	16	360273.94200	695633.77245
13	1600	3	1	9	360422.06950	695622.11300
14	1600	3	1	10	360466.35500	695808.73150
15	1800	3	1	14	360450.43635	695864.03950
16	1600	3	1	21	360575.66300	695696.56645
17	1600	3	1	28	360484.58935	695594.00200
18	1200	3	2	24	360714.73705	695050.53180
19	1200	2	1	15	360024.34700	695477.78500
20	1000	3	1	14	360036.19530	695680.08435
21	1200	2	1	31	360364.67100	695749.16150
22	1000	2	1	18	360148.63475	695764.51470
23	1000	2	1	4	360314.75650	695928 94215
25	1200	2	1	24	359649.89545	695651.30850
26	1400	3	2	33	358028.38331	695431.37823
27	1400	3	2	3	358024.50181	695390.01112
28	1800	4	2	21	357958.52000	695473.07800
29	1600	3	1	39	358033.84773	695589 29600
30	1400	3	2	17	358085.85800	695598.70200
31	1400	3	2	52	358199.54500	695573.33750
32	1400	2	1	12	358121.78639	695443.10158
33	1200	3	2	16	357946.45350	695678.89500
34	1600	3	2	9	358081.18600	695654.51146
35	1800	3	2	12	358041.29250	695718.12644
36	1800	3	3	24	357905.99450	695509.16350
37	1200	3	2	21	357813.15000	695549.97450
38	1400	2	1	17	357913.68700	695576.09850
39	1400	3	2	21	357753.31700	695610.40609
40	1600	2	1	6	357668.30400	695606.05950
41	1800	3	2	23	357652.85483	695739.76955
42	1800	2	1	39	357626.28076	695803.97350
43	1800	3	2	49	357604.55024	695581.05650
44	2000	3	2	19	357590.00150	695471.18000
45	1000	2	1	22	357681.32750	695405.85900
46	1200	2	1	9	357635.32650	695436.29500
47	1200	3	2	29	357786.99751	695464.09165
48	1200	2	1	3	357667.88250	695565.98500
49	1000	2	1	29	357691.10995	695746.94953
50	1600	2	1	9	357794.59921	695701.16003
51	2500	4	2	54	358260.68800	694877.28050

52	2400	4	2	24	358291.06090	694837.60410
53	2500	4	2	36	358304.15650	694805.00970
54	250	1	1	22	358360.57325	694751.60220
55	2000	3	1	17	358367.19900	694868.23350
56	2200	4	3	24	358230.09600	694885.04150
57	1870	3	1	44	358466.01925	694872.52850
58	1240	2	1	39	358454.62700	694869.50450
59	2050	4	2	26	358508.27100	694826.83900
60	1700	4	2	39	358051.58300	694967.74400
61	2260	4	2	24	358067.80185	694992.05380
62	1700	3	1	69	358178 01407	694805.18185
63	2296	4	2	2	358096.23050	694822.61000
64	1200	2	1	38	358064.16700	694880.45700
65	1796	3	1	37	358074.65200	694911.30800
66	1750	3	1	39	358292.23200	695380.91500
67	2500	4	2	44	358291.48900	695421.80800
68	1500	3	2	24	358221.19303	695407.61649
69	1450	3	2	32	358254.89500	695403.13700
70	2120	4	2	29	358266.79050	695377.06200
72	1700	3	1	25	358315.88000	695582.94400
73	1600	3	1	102	358464.33500	695198.62300
74	1434	3	2	44	358480.33000	695228.56050
75	1816	3	2	94	358385.28300	695166.67660
81	2600	3	2	26	358467.28650	696004.26500
82	3500	4	3	56	358586 06209	696045.89788
83	1600	2	1	6	358555.75450	696070.18955
84	3800	3	3	12	358356.11050	695902.26343
85	2000	2	1	29	358415.57050	695876.82200
86	3600	4	2	12	358413.20600	695828.46200
87	3400	4	3	27	358451.89085	695780.31300
88	2500	3	2	28	358392.39030	695794.92600
89	2200	3	2	36	358469.65550	695731.05650
90	3800	4	2	42	358212.56150	695915.88000
91	3500	4	3	22	358161.47404	695956.85100
92	2500	3	2	17	358141.83250	696014.47100
93	3000	4	2	12	358088.04131	695968.90850
94	1800	3	2	7	358079.81100	696006.37850
95	2000	3	2	36	358031.38250	695963.20550
96	3200	4	2	17	357997.42865	696065.56900
97	3000	4	2	14	357911.13841	696044.47300
98	2100	3	2	14	357806.94899	696123.00057
100	2600	4	2	3	357711.90600	696194.89050
101	2100	3	2	21	358993.50650	694971.21250
102	2200	3	2	51	359020.64800	694961.06000
103	2150	3	2	15	358984.49300	694946.76450
104	2500	4	2	25	359010.62353	694803.79530
105	2100	3	2	31	359079.27300	694917.75545
106	4400	3	2	54	359048.85050	694941.33250
107	2800	4	3	7	358950.11075	694994.72000
108	2600	4	2	29	358892.57250	694977.73950
109	2400	3	2	14	358887.19700	694933.91188
110	2200	3	2	16	358916.09300	695062.44750
111	2100	2	1	129	358924.99600	695130.25350
112	2400	4	2	3	358945.34900	695188.70800
113	2200	3	2	2	359018.28700	695084.79400
114	2100	4	2	24	358993.08150	695246.52720
116	7000	3	2	24	358883.21650	695117.52150

117	2600	4	3	3	358847.85100	695159.63050
118	2000	4	3	19	358815.63150	695241 84768
119	2400	4	2	28	358750.13100	695279.26700
120	1700	3	2	24	358719.70879	695272.69798
121	2600	3	2	24	358579 37550	694920.55950
122	2400	4	2	9	358594.58400	694819.01500
123	2400	4	2	39	358577.76550	694778.14100
124	200	1	1	24	358576 64150	694745.59400
125	1000	2	1	14	358599.61000	694734.75550
126	1600	2	2	6	356640.55550	695435.72450
127	5000	3	2	9	356793.16050	695406.23150
128	1800	3	2	18	356928.89445	695445.17288
129	1600	2	1	19	356993.29300	695396.80000
130	1000	4	1	16	356971.01200	695477.33400
131	1900	3	2	49	357023 00909	695466.73600
132	2000	1	2	14	357087.58700	695442.90300
133	2100	4	2	26	357061.42450	695507 21150
134	2000	4	1	9	357051.68750	695540.89350
135	2100	3	2	17	357013.57483	695570.48600
136	1600	2	1	14	357199.70150	695551.48850
137	1800	3	2	40	357138.96900	695551.74500
138	1900	3	2	7	356335.22700	695502.42900
139	2000	3	1	54	356266.12040	695489 49400
140	1800	2	1	102	356221.78100	695543.23790
141	1700	3	1	4	356246.35000	695710.15700
142	1600	2	1	44	356210.28125	695734 31900
143	1900	3	1	2	356144.12550	695608.14150
144	1800	3	1	29	356029.48490	695539.01650
144	1600	2	1	14	356039.87350	695595.89600
145	1800	4	2	24	356094 16300	695715 10850
145	1800	4	2	2	356011.64115	695821.77500
146	1750	3	1	29	355919.75100	695760.72250
147	2000	3	1	22	355886 61840	695689.70450
148	2000	2	1	14	355793 93455	695632.46160
149	2100	2	1	5	359295.82550	694591.49150
150	1900	2	1	9	359327.69050	694573.32550
151	1200	3	2	9	359230.71950	694608.15625
152	1300	3	2	6	359423.67150	694567.93800
153	1600	3	1	13	359106.54000	694658.75850
154	1400	4	2	19	359261.75700	694695.24945
155	1350	4	2	29	359270.36625	694774.80250
156	1900	4	2	24	359202 09600	694797.14205
157	2100	3	2	24	359246.21600	694791.76550
158	2250	3	1	5	359187.98100	694783.80240
159	1896	3	2	15	359159.90425	694758.45200
160	1750	4	2	29	359147.17600	694803.73150
161	1500	3	3	24	359258.61700	694860.55750
162	2000	3	2	14	359237.69300	694869.46065
163	1950	4	2	10	359368.65900	694808.36750
164	1700	4	2	19	359421 44650	694790.29700
165	2500	3	2	14	359417.39350	694728.77800
166	2208	3	1	24	359483.13150	694794.18835
167	1950	3	2	24	359461.25875	694849.32915
168	1400	3	1	10	359334.36200	695064.66750
169	1520	3	2	24	359348.39110	695005.98610
170	1600	3	2	14	359361.70770	694949.40950
171	4500	4	3	14	359282.13350	695024.47275

172	1490	4	2	34	359230.61510	695033.33130
173	2150	3	1	24	359149.42965	695009 03850
174	2500	3	2	44	359887.58700	694693.39950
175	1820	3	2	19	360039 63915	694766 91050
176	1600	4	2	19	359939.32890	694801.24820
177	1200	3	2	14	360005.69160	694869.69790
178	1200	3	2	24	360082.24450	694833.10155
179	1300	3	2	32	360125.39145	695119 60865
180	1200	3	2	19	360131.23000	695203.37235
181	1600	2	2	8	359983.78270	695240.16000
183	1600	3	2	14	360061.22650	695075 04495
184	1600	4	2	16	359771.03600	695161.35760
185	8000	3	2	14	359775.72015	695089.37215
186	1400	4	2	6	359898.38720	695060.24790
187	1200	3	2	24	359930 63730	694981.77975
188	1100	3	2	14	359786.89540	694745.37250
190	1200	3	2	10	359719 71850	694795.90200
191	900	3	2	6	359764.58880	694962.40425
192	1600	3	2	9	359765.56400	695019.77950
193	1800	4	2	15	359822.59150	694961 68280
194	1600	2	2	22	359911.98365	695169.13765
195	1000	2	1	15	359750.42530	694588.79720
196	800	2	2	6	359731.34850	694539.31435
197	800	2	1	8	359828.34785	694523.25300
198	400	2	1	24	359895.50100	694555.83500
199	800	2	1	11	360097.67650	694700.25019
199	800	3	2	14	360287.01100	694677.17550
201	1600	2	2	24	360239.84850	694708.55000
202	1400	3	2	4	360202.47750	694819.82100
203	1600	3	1	4	360201.95150	694896.74200
204	1800	3	1	18	360302.89200	694888.23155
205	1200	4	3	14	360276.15250	694813 33610
206	1400	3	2	8	360405.76550	694804.10800
207	2000	3	3	8	360481.42055	694700.61465
208	1200	3	3	9	360601.31250	694731.34100
209	1800	2	1	11	360560.08850	695050.17630
210	1800	2	2	11	360489.77200	695145.33350
211	1400	3	2	27	360215.81850	695165.43950
212	1400	3	3	15	360300.20550	694641.47505
213	1600	2	1	18	360683.54150	694560.68785
214	1800	4	3	13	360777.90325	694577.76345
215	1600	2	2	22	360700.82255	694735.36250
216	2800	3	2	1	360797 82600	694880.81400
217	1600	3	2	12	360832.03000	694983.38700
218	1800	3	3	8	360920.18230	694920.14400
219	1600	2	1	16	360558.56050	694432.29550
220	1800	2	1	10	360615.06450	694517.15600
221	1200	2	1	16	360479.80910	694539.48460
222	800	2	1	9	360230.77300	694485.28135
223	1000	2	1	19	362715.52250	694587.01940
224	1000	4	2	14	362696.81300	694502.54160
226	1200	4	1	4	362685.91940	694630.61195
227	1400	4	3	8	362516 05105	694799.07650
228	1400	3	2	15	362379.53460	694520.90010
229	4800	4	2	14	362372.06850	694731 15850
230	1200	3	2	24	362303 81550	694756.05650
231	1200	3	1	4	362259.85350	694599.45100

232	1400	3	2	9	362198.78200	694515.10800
233	800	2	2	24	362681.40925	694725 86750
234	1400	2	2	7	361941.06395	694573.88760
235	1600	2	2	30	361774 63260	694134.74370
236	1600	2	2	6	362010.58060	693918.66600
237	1600	4	2	14	361781.67255	694772.83345
238	1400	3	2	3	361716.17050	694584.26300
239	1600	2	2	19	361548.77950	694663.11900
240	1800	2	2	14	361380.17850	694778.53150
241	1600	3	2	6	361325.82100	694720.69850
242	1600	3	2	39	361099.77215	694541.73550
243	1600	4	3	17	361634 02150	694262.72050
246	1400	3	2	24	361692.99850	694966.89250
247	800	2	1	9	362180.44880	694581.59160
248	800	2	1	14	362003.97350	694566 37250
249	1000	2	1	9	361886.56650	694472.02350
250	1000	2	1	8	361865.30045	694389.05685
251	1200	2	1	36	359293.76640	695971.65180
253	2000	2	2	31	359257.53325	695982.79670
254	1100	2	1	11	359265.23100	695937.05350
255	1600	4	3	45	359248.99750	695930.52100
256	1000	4	2	31	359191.09250	695941.39600
257	1200	2	1	24	359276.51465	695872 52690
258	1200	4	2	26	359257.35650	695848.56275
259	1200	4	3	37	359324.42200	695866.40750
260	1500	4	2	36	359370.13526	695900.23425
261	1200	2	1	34	359382.37370	695909.35010
262	1200	2	1	23	359370.83020	695869 63165
263	1000	3	1	28	359399.45400	695894.09405
264	1000	3	1	40	359426.06550	695932.70400
265	1100	3	1	30	359404.99115	695816.40870
266	1000	2	1	28	359372 27600	695817.35000
267	1200	2	1	10	359227.72250	695820.36950
268	1200	2	2	14	359212.07400	695822.83345
269	1200	3	2	4	359185.41450	695780 61450
270	1000	3	2	24	359185.70700	695745.50445
271	936	2	2	2	359164.51695	695708.48030
272	1000	3	2	14	359243.19855	695615.44850
273	1000	2	2	24	359262 61700	695578.61500
274	600	1	1	41	359328.92900	695673.57085
275	1600	4	1	32	359412.57500	695677.53280
276	800	3	1	29	358953.45950	695621.94900
277	600	1	1	24	358937.53350	695655.12050
278	1296	2	1	20	358930.80760	695675.69600
279	900	2	1	17	358896 81095	695685.32000
280	1000	4	1	36	358842.30350	695654.32850
281	1000	3	1	34	358839.65230	695674.22500
282	500	2	1	14	358822.68000	695705.46500
283	1200	3	1	12	358785.88205	695821.60685
284	800	2	1	6	358776.92500	695781.63000
285	200	2	1	24	358775.58550	695691.56250
286	1200	3	2	31	358655.81130	695804.71900
287	1000	3	2	42	358668.44615	695775.35590
288	900	2	1	9	358672.71050	695762.94100
289	300	2	1	28	358737.99786	695706.61650
290	1000	3	2	5	358711.30560	695709.87400
291	300	2	1	14	358638.21720	695715.78050

292	1000	4	2	18	358757.30800	695646.92300
293	1500	4	1	69	358918.91480	695623.83350
294	500	2	1	19	358927.46450	695660.33600
295	700	2	1	7	358965.57150	695699.64235
296	200	1	1	29	359046.72380	695671.06070
297	1200	3	2	7	358841.73350	695635.95000
298	1100	3	2	14	358830.81225	695548.52160
299	1200	3	2	26	358929.07000	695744.40480
300	700	3	1	26	358988.33800	695680.02000
301	1000	3	1	22	362834.98900	693793.11450
302	1000	4	1	24	362933.15715	693799.84720
303	1600	4	1	24	362889.51975	693875.98695
304	800	2	1	4	362910.64220	693965.07030
305	500	2	1	2	362813.39475	694020.91645
306	1200	1	1	14	362734.80365	693959.74240
307	600	2	1	4	362990.80595	694184.97185
308	800	2	1	17	363037.51825	694230.68935
309	500	1	1	24	363130.66480	694228.59105
310	1000	1	1	33	363036.89510	694200.22495
311	1000	2	1	10	363074.22410	694140.52190
312	300	1	1	14	363176.70400	694193.29315
313	500	1	1	8	363232.56505	694138.96500
314	400	1	1	4	362929.19795	694135.75465
315	700	1	1	24	362796.71180	694179.98865
316	1200	2	1	34	362834.05695	694182.00155
317	900	1	1	2	362570.61750	694217.43100
318	500	2	1	8	362550.19100	694190.97500
319	600	1	1	14	362557.81700	694142.74740
320	700	1	1	14	362509.15950	694110.16425
321	1200	2	1	19	362427.75500	694150.86605
322	1000	1	1	14	362438.98600	694094.99100
323	600	1	1	9	362434.22155	694013.71000
324	700	1	1	12	362361.77640	693998.30040
325	300	1	0	9	362390.31400	694026.80220
326	300	1	0	11	358913.48705	697352.05545
327	1000	1	1	23	358923.81500	697315.02880
328	600	1	1	17	358950.04200	697306.45100
329	600	2	1	6	359042.61550	697299.92350
330	900	2	1	48	359018.96200	697326.69000
331	1200	3	2	19	359027.29595	697249.16505
332	2000	4	3	7	358997.51100	697257.72150
333	1000	3	2	24	359020.03500	697537.26550
334	1400	4	2	6	359032.02495	697568.91050
336	800	2	1	14	359037.45800	697600.02200
337	200	1	1	9	359022.93050	697618.64850
338	800	3	1	34	359074.26700	697622.65450
339	500	2	1	5	359065.10550	697946.33600
340	300	2	1	26	359055.28250	697962.14850
341	6000	3	1	18	359046.83750	697954.79000
342	1200	3	2	26	359051.58815	698011.76150
343	800	3	2	24	359062.80450	698046.69500
344	600	2	1	19	359032.15250	698000.04450
345	1000	2	2	22	359043.59300	698254.91950
346	1250	3	2	8	359009.50650	698264.64400
347	1200	2	2	10	359031.36295	698312.43800
348	1800	2	1	16	358979.08006	698309.42740
349	500	2	1	3	358940.21200	698374.11450

350	4000	2	1	14	358961.72820	698398 98655
351	400	2	1	12	357469 82450	696196.02343
352	700	2	1	18	357519.18050	696135.67450
353	900	3	1	3	357446.84250	696133 11550
354	1200	3	1	13	357455 65626	696110 33197
356	1000	3	1	39	357488 45073	696014.71500
357	1080	4	3	18	357522.21150	695870.11200
358	600	2	1	13	357472.95555	695904 17275
359	800	2	1	14	357464.03653	695766.46100
360	800	3	2	15	357448.81200	695749.51950
361	800	3	1	5	357400.38819	695742.58650
362	400	2	1	12	357329.31950	695746.37950
363	800	2	1	32	357407.38694	695716.08795
364	1500	1	1	16	357300.48450	695482.17250
365	800	3	2	11	357322.53522	695449.94900
366	800	2	2	22	357283.26450	695446.73800
367	700	3	1	59	357335.15179	695443 90000
368	600	2	1	7	357355.05905	695189.03600
369	600	1	1	4	357322.76190	695189.57620
370	300	1	1	44	357301.47645	695140 60260
371	400	2	1	12	357339.44390	695097.79305
372	400	1	1	14	357590.67505	695061.42300
373	600	3	1	14	357653.67000	695000.33350
374	500	3	1	9	357602.16900	695022.86200
375	800	3	1	14	357651.23300	694975.01500
376	1440	3	1	14	358553.27760	698194.38060
377	1000	2	1	6	358529.10545	698212.10360
378	720	1	1	19	358134.31005	697776.45430
379	1080	2	1	14	358318.32300	697930.94160
380	1440	2	1	14	358325.61400	697925.56850
381	540	2	1	6	358520.92240	698216 25470
382	1800	3	1	10	358606 68970	698355.63965
383	1800	3	1	13	358638.50680	698344.55195
384	900	2	1	9	358632.54000	698358.33545
385	1260	2	1	8	358533.38150	698364.21200
386	1260	2	2	19	358532.37000	698350.65700
387	1000	1	1	6	358545.94750	698360.39300
388	540	1	1	9	358555.24150	698366.27700
389	540	1	1	9	358563.55250	698351 22650
390	1260	2	1	24	358557.14800	698340.24450
391	1980	2	1	6	358489.03600	698369.17050
392	1440	2	1	6	358462.03850	698351.40550
393	2160	4	1	9	358390.09140	698411.31700
394	1440	3	1	13	358385.92565	698422.17895
395	1080	2	1	17	358375.81180	698423.83680
396	1260	2	1	6	357177.87850	697126.57600
397	1440	2	1	14	357245.79540	697007.78040
398	1400	2	1	9	357216.83615	696978 31740
399	1440	3	1	11	357156.63365	696987.15500
400	1400	2	1	21	357216.76750	697204.87950
401	1400	2	1	4	357236.61720	697256.96420
402	1440	2	1	10	357231.21920	697278.81865
403	1440	2	1	19	357220.78220	697322.49875
404	1260	3	1	8	357189.93940	697148.76950
405	1350	2	1	24	357205 07525	696980.30875
406	1440	2	1	16	357191.09335	696966.38620
407	1500	3	1	10	357206.52995	697154.02870

408	1440	2	1	22	357191.10500	696995.50755
409	720	1	1	3	357283.05620	697301.98820
410	1260	2	1	12	357229.25150	696971.39980
411	2400	4	2	19	357773.52500	696962.48520
412	3000	4	3	19	357813 19850	696935 03900
413	720	1	1	13	357808.17500	696861.58600
414	2400	3	1	16	357808.36550	696849.64840
416	600	1	1	11	359573.22465	699428.28285
417	720	2	1	2	359573.65540	699439.77190
418	1500	2	1	14	359591.73625	699420.27235
419	1800	2	1	14	359598.03485	699429.65305
420	1440	3	1	9	359556.83490	699384.05520
421	1080	2	1	9	359549.58070	699352.48665
422	1440	2	1	13	359602.32630	699331.20405
423	1440	2	1	19	359609.45990	699335.72280
424	1080	2	2	4	359152.59250	699144.38000
425	1080	2	1	4	359536.84810	699031.29835
426	1440	2	2	14	359119.16290	699120.49050
427	1440	2	2	14	359129.35915	699113.11425
428	1440	3	2	10	359140.51175	699083 84825
429	1800	2	1	14	359141.25910	699060 37220
430	1850	2	1	18	359172.16710	699102.13900
431	2000	2	1	14	359194.18350	699045.52300
432	1800	2	2	19	359651.44475	699605.49875
433	1620	2	1	3	359623.74580	699575.78235
434	1620	2	1	18	359608.87968	699607.57723
435	1440	3	2	14	359549.70825	699477.80490
436	3600	3	1	14	359487.58050	696637 10550
437	1200	2	1	14	359485.09975	696646.68475
438	720	1	1	7	359359.22950	696609.06800
439	1440	1	1	6	359706.72750	697507.33700
440	1440	2	1	9	360099 49500	697203.29950
441	1440	2	1	5	360073.66000	697192.73750
442	1440	3	1	14	359820.08490	697217.67100
443	2340	2	1	12	359712.52650	697226.52050
444	3960	3	2	8	359716.07400	697240 87000
445	3960	4	2	6	359574 25820	697246.04510
446	3600	3	3	14	359696.77150	697270.95220
447	1800	3	2	24	359580.99000	697121.34300
448	2520	3	1	9	359594.94650	697074.65350
449	1440	3	1	3	359612.57550	697069.45000
450	1800	3	1	4	359647.93600	697060.54950
451	1800	2	1	6	359677.51995	697073.76150
452	2160	3	1	6	359666.36630	697074.48800
453	1440	2	1	12	359617.26800	697513.65700
454	1440	2	1	14	359629.71900	697512.10900
455	1440	1	1	14	359726.86600	697481.53650
456	1080	3	1	19	358702.02335	696721.05920
457	1440	4	2	8	358938.39600	696886.40700
458	720	2	1	19	358802.69620	696752.06700
459	700	1	1	19	358814.40500	696749.07350
460	700	1	1	9	358803.73220	696734.87335
461	500	1	1	24	358805.73495	696782 95900
462	1800	3	1	18	358956.49600	696923.72200
463	500	1	1	6	358848.16619	697014.31500
464	1440	3	1	18	358764.49480	697029.49790
465	1440	3	1	13	358912 99650	697028.65570

466	1080	2	1	24	358910.96600	696956.95700
467	1440	2	1	16	358909.99175	696911.92300
468	4320	4	3	23	358894.55450	696892.59650
469	720	2	1	6	358898.65550	696906.77300
470	1300	4	2	12	358911.30750	696947.42585
471	1080	4	1	12	358818.29750	697079.59950
472	1440	3	1	35	358914.34600	696889.44815
473	2160	2	1	8	358742.51870	696992.45760
474	2880	1	1	42	358754.00810	696972.50025
475	1800	3	1	15	358733.10285	696944.79970
476	720	2	1	9	356079.17700	696238.83035
477	1080	2	1	10	356081 51200	696247.93620
478	720	2	1	9	356058.85600	696245.64350
479	1800	3	1	14	356077.25545	696165.47200
480	1440	4	2	5	356095.29800	696139.93535
481	1440	2	1	19	355902.60700	696271.73900
482	2160	3	1	9	355908.17750	696339.80450
483	2880	3	1	19	355825.34150	696249.58850
485	2160	3	2	9	355599.24573	696228.97000
486	1440	3	1	29	355492.62090	696277.02855
487	2160	3	1	24	355504.17740	696286.90900
488	1800	2	2	7	355630.52850	696520.20250
489	3000	3	2	24	355624.08150	696480.82800
489	1440	2	1	18	355587.95225	696397.46120
490	1440	4	2	10	355553.87070	696383.60750
491	2700	2	1	15	356400.65850	696640.78600
492	1400	4	3	6	356755.08700	696835.68050
493	800	2	1	29	356739.65575	696559.89630
494	1500	2	1	9	356750.66150	696726.60150
495	1860	3	2	9	356423.02955	696763 46250

Table: Neighborhood Attributes

HOUSE_ID	RES_LUSE	COM_LUSE	COMMU_LU	DRAINAGE
1	43.83	7.69	3.15	10.315
2	43.83	7.69	3.15	9 13
3	43.83	7.69	3 15	12.016
4	43.83	7.69	3.15	25.048
5	43.83	7.69	3.15	4.379
6	43.83	7 69	3.15	78.413
7	43.83	7.69	3.15	14 293
8	43.83	7.69	3.15	6 176
9	43 83	7.69	3.15	10.834
10	43.83	7.69	3.15	10.946
11	43.83	7.69	3.15	12.021
12	43.83	7.69	3.15	7.734
13	43.83	7.69	3 15	14.922
14	43.83	7.69	3.15	15.672
15	43.83	7.69	3.15	11.294
16	43.83	7 69	3.15	133.006
17	43.83	7.69	3.15	5.056
18	43.83	7.69	3.15	7.655
19	43.83	7.69	3.15	8.869
20	43.83	7.69	3.15	64.005
21	43.83	7.69	3 15	26.247
22	43.83	7.69	3.15	6.869
23	43.83	7 69	3.15	53.163
25	43.83	7.69	3.15	19.717
26	45.35	8.63	5.31	4 473
27	45.35	8.63	5.31	7.627
28	45.35	8 63	5.31	41.133
29	45.35	8.63	5.31	17.918
30	45.35	8.63	5.31	21.429
31	45.35	8 63	5.31	11.249
32	45.35	8 63	5.31	4.714
33	45.35	8.63	5.31	11.435
34	45.35	8.63	5.31	8.503
35	45.35	8.63	5.31	5.448
36	45.35	8.63	5.31	17.171
37	45.35	8.63	5.31	10.823
38	45.35	8.63	5.31	35.588
39	45.35	8.63	5.31	4.735
40	45.35	8.63	5.31	7.94
41	45.35	8.63	5.31	4 989
42	45.35	8 63	5.31	15.82
43	45.35	8.63	5.31	12.634
44	45.35	8.63	5.31	10.326
45	45.35	8.63	5.31	14.863
46	45 35	8.63	5.31	6.542
47	45.35	8 63	5.31	6.362
48	45.35	8.63	5.31	19.895
49	45 35	8.63	5.31	12.744
50	45.35	8.63	5.31	5.771
51	43.83	7.69	3.15	9 05
52	43.83	7.69	3.15	35.263

53	43.83	7.69	3 15	16.063
54	43.83	7.69	3 15	7.885
55	43.83	7.69	3.15	8.404
56	43.83	7.69	3.15	5 617
57	43.83	7.69	3.15	17.525
58	43.83	7.69	3 15	9.8
59	43.83	7.69	3.15	17.561
60	43.83	7.69	3.15	52.453
61	43.83	7.69	3.15	62.387
62	43.83	7.69	3.15	13.553
63	43.83	7.69	3.15	3.345
64	43.83	7.69	3.15	26.844
65	43.83	7.69	3.15	11.619
66	43.83	7.69	3.15	7.151
67	43.83	7.69	3.15	11.775
68	43.83	7.69	3 15	30.512
69	43.83	7.69	3.15	8.926
70	43.83	7.69	3.15	5.028
72	43.83	7.69	3.15	6.612
73	43.83	7.69	3.15	4.332
74	43.83	7.69	3.15	9.721
75	43.83	7.69	3.15	6.054
81	45.35	8.63	5.31	4.265
82	45.35	8.63	5.31	21.144
83	45.35	8.63	5.31	12.091
84	45 35	8.63	5.31	10.91
85	45.35	8.63	5 31	3.268
86	45.35	8.63	5.31	4.661
87	45.35	8.63	5.31	11 16
88	45.35	8.63	5.31	8 506
89	45.35	8.63	5.31	4.204
90	45.35	8.63	5.31	16.333
91	45.35	8.63	5.31	17.047
92	45 35	8.63	5.31	7.113
93	45.35	8.63	5.31	6.048
94	45.35	8.63	5.31	7.673
95	45.35	8.63	5.31	7.056
96	45.35	8 63	5.31	8.168
97	45.35	8.63	5.31	26 668
98	45.35	8.63	5.31	14.309
100	45.35	8.63	5.31	29.159
101	43.83	7.69	3.15	36.131
102	43.83	7.69	3.15	64.846
103	43.83	7.69	3.15	40.666
104	43.83	7.69	3.15	19.814
105	43.83	7.69	3.15	13.463
106	43.83	7.69	3.15	47.364
107	43.83	7.69	3.15	12.641
108	43.83	7.69	3.15	14.44
109	43.83	7.69	3.15	7.428
110	43.83	7.69	3.15	6.511
111	43.83	7.69	3.15	7.357
112	43.83	7.69	3.15	6.978
113	43.83	7.69	3.15	8.107

114	43.83	7.69	3.15	12.41
116	43.83	7.69	3.15	4.081
117	43.83	7.69	3.15	7.758
118	43.83	7.69	3.15	7.617
119	43.83	7.69	3.15	7.977
120	43.83	7.69	3.15	16.121
121	43.83	7.69	3.15	4.319
122	43.83	7.69	3 15	11 317
123	43.83	7.69	3.15	9.784
124	43.83	7.69	3.15	16.77
125	43.83	7.69	3.15	16.111
126	45.35	8.63	5.31	13.417
127	45.35	8.63	5.31	14.449
128	45.35	8.63	5.31	18.287
129	45.35	8.63	5.31	46.802
130	45.35	8.63	5.31	6.826
131	45.35	8.63	5.31	11.839
132	45.35	8 63	5 31	'9.838
133	45.35	8.63	5.31	8.182
134	45.35	8.63	5.31	7.22
135	45.35	8.63	5.31	10.876
136	45.35	8.63	5.31	8.921
137	45.35	8.63	5.31	21.027
138	45 35	8.63	5.31	28.264
139	45.35	8.63	5.31	10 673
140	45 35	8.63	5.31	10 91
141	45.35	8.63	5.31	10 081
142	45.35	8.63	5.31	8.624
143	45.35	8.63	5.31	12 359
144	45.35	8.63	5.31	15.593
144	28.41	3.54	1.03	8.782
145	45 35	8.63	5.31	9.151
145	28.41	3.54	1.03	11.121
146	45.35	8.63	5.31	14.032
147	45.35	8.63	5.31	10 517
148	45.35	8.63	5.31	5.732
149	45.35	8 63	5.31	57.903
150	45.35	8.63	5.31	60.969
151	43.83	7.69	3.15	51.027
152	43.83	7.69	3.15	75.049
153	43.83	7 69	3.15	33 122
154	43.83	7.69	3.15	12.8
155	43.83	7 69	3.15	6.651
156	43.83	7.69	3.15	22.137
157	43.83	7.69	3.15	34.432
158	43.83	7.69	3.15	7.571
159	43.83	7.69	3.15	9.211
160	43.83	7 69	3.15	10 269
161	43.83	7.69	3.15	9.057
162	43.83	7.69	3.15	10.862
163	43.83	7.69	3.15	9.261
164	43.83	7.69	3 15	5.502
165	43.83	7.69	3.15	4.494
166	43.83	7.69	3.15	10.719

167	43.83	7.69	3.15	8.552
168	43.83	7.69	3.15	5.076
169	43.83	7.69	3.15	8.326
170	43.83	7.69	3.15	9.721
171	43.83	7.69	3.15	5.555
172	43.83	7.69	3.15	9.068
173	43.83	7.69	3.15	32.312
174	43.83	7.69	3.15	4.907
175	43 83	7 69	3.15	13 81
176	43.83	7.69	3.15	13.291
177	43.83	7.69	3.15	7.873
178	43.83	7.69	3.15	6.629
179	43.83	7.69	3.15	17.35
180	43.83	7.69	3.15	10.41
181	43.83	7.69	3.15	24.312
183	43.83	7.69	3.15	12 572
184	43.83	7.69	3.15	10.223
185	43.83	7.69	3.15	11.217
186	43.83	7.69	3.15	61.032
187	43.83	7.69	3.15	6 88
188	43.83	7.69	3.15	11.943
190	43.83	7.69	3.15	1.267
191	43.83	7.69	3.15	14 652
192	43.83	7.69	3.15	8.324
193	43.83	7.69	3.15	72.223
194	43.83	7.69	3.15	43 803
195	43.83	7.69	3.15	46 763
196	43.83	7.69	3.15	75.565
197	43.83	7.69	3.15	7.069
198	43 83	7.69	3.15	17.872
199	43.83	7.69	3.15	11 62
199	43.83	7.69	3.15	9.428
201	43.83	7.69	3.15	19.156
202	43.83	7.69	3 15	4.107
203	43.83	7.69	3.15	9.115
204	43.83	7.69	3.15	6.948
205	43.83	7.69	3.15	11.671
206	43.83	7.69	3.15	7.688
207	43.83	7.69	3.15	7.836
208	43.83	7.69	3.15	75.004
209	43.83	7.69	3.15	14.57
210	43.83	7.69	3.15	17.025
211	43 83	7.69	3.15	32.226
212	43.83	7 69	3.15	9.708
213	43.83	7.69	3.15	2.513
214	43.83	7.69	3.15	15.673
215	43.83	7.69	3.15	5.545
216	43.83	7.69	3.15	19.9
217	43.83	7.69	3.15	9.691
218	43.83	7.69	3.15	22.45
219	43.83	7.69	3.15	33.907
220	43.83	7.69	3.15	42.024
221	43.83	7.69	3.15	7.825
222	43.83	7.69	3.15	57.721

223	43.83	7.69	3.15	236.491
224	43.83	7.69	3.15	281.111
226	28.41	3.54	1.03	262.564
227	28.41	3.54	1.03	356.037
228	28.41	3.54	1.03	255.564
229	28.41	3.54	1.03	362.385
230	28.41	3.54	1.03	296.129
231	28.41	3.54	1.03	256.474
232	28.41	3.54	1.03	165.3
233	28.41	3.54	1.03	284.318
234	28.41	3.54	1.03	5.178
235	28.41	3.54	1.03	235.681
236	28.41	3.54	1.03	284.327
237	28.41	3.54	1.03	14.412
238	28.41	3.54	1.03	12.135
239	28.41	3.54	1.03	8.048
240	28.41	3.54	1.03	6.763
241	28.41	3.54	1.03	19.305
242	28.41	3.54	1.03	36.67
243	28.41	3.54	1.03	46.323
246	28.41	3.54	1.03	11.481
247	28.41	3.54	1.03	181.218
248	28.41	3.54	1.03	34.281
249	28.41	3.54	1.03	101.691
250	28.41	3.54	1.03	142.582
251	43.83	7.69	3.15	16.252
253	43.83	7.69	3.15	18.772
254	43.83	7.69	3.15	8.658
255	43.83	7.69	3.15	8.35
256	43.83	7.69	3.15	11.814
257	43.83	7.69	3.15	12.559
258	43.83	7.69	3.15	26.321
259	43.83	7.69	3.15	21.468
260	43.83	7.69	3.15	16.125
261	43.83	7.69	3.15	27.69
262	43.83	7.69	3.15	12.111
263	43.83	7.69	3.15	25.21
264	43.83	7.69	3.15	61.699
265	43.83	7.69	3.15	6.333
266	43.83	7.69	3.15	28.256
267	43.83	7.69	3.15	38.122
268	43.83	7.69	3.15	46.122
269	43.83	7.69	3.15	25.039
270	43.83	7.69	3.15	5.822
271	43.83	7.69	3.15	8.297
272	43.83	7.69	3.15	14.232
273	43.83	7.69	3.15	9.363
274	43.83	7.69	3.15	22.517
275	43.83	7.69	3.15	9.53
276	43.83	7.69	3.15	9.714
277	43.83	7.69	3.15	5.675
278	43.83	7.69	3.15	9.362
279	43.83	7.69	3.15	5.59
280	43.83	7.69	3.15	9.185

281	43.83	7.69	3.15	10.475
282	43.83	7.69	3.15	10 347
283	43.83	7.69	3 15	8.819
284	43.83	7.69	3.15	11.129
285	43.83	7 69	3.15	31.729
286	43.83	7 69	3.15	3.339
287	43.83	7.69	3.15	12.161
288	43.83	7.69	3.15	5.568
289	43.83	7.69	3.15	11.654
290	43.83	7.69	3.15	2.455
291	43 83	7.69	3.15	8.723
292	43.83	7.69	3.15	2.3
293	43.83	7.69	3.15	6 187
294	43.83	7.69	3.15	4 871
295	43.83	7 69	3.15	12.407
296	43.83	7.69	3.15	2.554
297	43.83	7.69	3.15	8.591
298	43.83	7.69	3.15	14.808
299	43 83	7.69	3.15	15.137
300	43.83	7 69	3.15	3.498
301	28.41	3.54	1.03	733 912
302	28.41	3.54	1.03	760.067
303	28.41	3.54	1.03	702.235
304	28.41	3.54	1 03	610.965
305	28.41	3.54	1.03	587.109
306	28.41	3.54	1.03	551.251
307	28.41	3 54	1.03	377.107
308	28.41	3.54	1.03	320.673
309	28.41	3.54	1.03	289.437
310	28.41	3.54	1.03	349.663
311	28.41	3.54	1.03	391.414
312	28.41	3.54	1.03	307.374
313	28.41	3.54	1.03	344.188
314	28.41	3.54	1.03	444 424
315	28.41	3.54	1.03	463.4
316	28.41	3.54	1.03	442.848
317	28.41	3.54	1.03	290.39
318	28.41	3.54	1.03	278.003
319	28.41	3.54	1.03	304.047
320	28.41	3.54	1.03	280.408
321	28.41	3.54	1 03	191.913
322	28.41	3.54	1.03	240.513
323	28.41	3.54	1.03	305 565
324	28.41	3.54	1.03	283.729
325	28.41	3.54	1.03	274.864
326	40.56	1 83	2.21	60.968
327	40.56	1.83	2.21	70.425
328	40.56	1.83	2.21	50 42
329	40.56	1.83	2.21	7 107
330	40.56	1.83	2 21	13 184
331	40.56	1.83	2.21	8 961
332	40.56	1.83	2.21	14.007
333	40.56	1 83	2.21	7.847
334	40.56	1.83	2.21	10.378

336	40.56	1.83	2.21	7.734
337	40.56	1.83	2.21	10.201
338	40.56	1.83	2 21	38 172
339	40.56	1.83	2.21	7.616
340	40 56	1.83	2.21	16.242
341	40.56	1.83	2.21	6.16
342	40.56	1.83	2 21	7.199
343	40.56	1.83	2.21	22.989
344	40.56	1.83	2.21	11.978
345	40.56	1.83	2.21	68.692
346	40.56	1.83	2.21	33.74
347	40.56	1.83	2.21	41.814
348	40.56	1.83	2.21	4 385
349	40.56	1.83	2.21	73.786
350	40.56	1.83	2.21	66.978
351	45.35	8.63	5.31	2 544
352	45.35	8.63	5.31	9 009
353	45.35	8.63	5.31	7.455
354	45.35	8.63	5.31	7.942
356	45.35	8.63	5.31	15.349
357	45 35	8.63	5.31	10.432
358	45.35	8.63	5.31	16.821
359	45.35	8.63	5.31	4.913
360	45 35	8.63	5.31	5 251
361	45.35	8.63	5.31	4.231
362	45.35	8.63	5.31	6 231
363	45 35	8.63	5.31	5.29
364	45.35	8.63	5.31	4.751
365	45.35	8.63	5.31	8.247
366	45.35	8.63	5.31	9.601
367	45.35	8.63	5.31	8.831
368	45.35	8 63	5.31	11 345
369	45.35	8.63	5.31	3.351
370	45.35	8.63	5.31	16.069
371	45.35	8 63	5.31	21 694
372	45.35	8.63	5 31	3.063
373	45.35	8.63	5.31	6 881
374	45 35	8.63	5.31	4.482
375	45.35	8.63	5.31	3.268
376	40.56	1.83	2.21	19.347
377	40.56	1.83	2.21	3.423
378	40.56	1.83	2.21	135.887
379	40.56	1.83	2.21	73.428
380	40.56	1.83	2.21	70 348
381	40.56	1.83	2.21	6.155
382	40.56	1.83	2.21	34.198
383	40.56	1.83	2.21	20.396
384	40.56	1.83	2.21	30.15
385	40.56	1.83	2.21	45.353
386	40 56	1.83	2.21	36.26
387	40.56	1.83	2 21	34.983
388	40.56	1.83	2.21	37.264
389	40.56	1.83	2 21	20.816
390	40.56	1.83	2.21	11.931

391	40.56	1.83	2.21	75.062
392	40.56	1.83	2.21	49.846
393	40.56	1.83	2.21	94.475
394	40 56	1.83	2.21	105.916
395	40.56	1.83	2.21	109.913
396	40.56	1.83	2.21	12.634
397	40.56	1.83	2.21	25 726
398	40.56	1.83	2.21	6.243
399	40.56	1 83	2.21	7.471
400	40.56	1.83	2.21	7.08
401	40 56	1.83	2.21	52.316
402	40 56	1.83	2.21	70.394
403	40.56	1.83	2 21	111.474
404	40.56	1.83	2.21	6.92
405	40.56	1.83	2.21	5.449
406	40.56	1.83	2.21	20.783
407	40.56	1.83	2.21	8.304
408	40.56	1.83	2.21	6.083
409	40.56	1.83	2.21	115.819
410	40.56	1.83	2.21	11.872
411	40.56	1.83	2.21	13.124
412	40.56	1.83	2.21	9.693
413	40.56	1.83	2.21	10.569
414	40.56	1.83	2.21	13.18
416	27.04	1.36	0.19	379 94
417	27.04	1.36	0.19	371.876
418	27.04	1.36	0.19	398.463
419	27.04	1.36	0.19	396.218
420	27.04	1.36	0.19	403.533
421	27.04	1.36	0.19	425.222
422	27.04	1.36	0.19	473.121
423	27 04	1.36	0.19	473.924
424	27.04	1.36	0.19	75.354
425	27.04	1.36	0.19	432 498
426	27 04	1 36	0.19	34.942
427	27.04	1.36	0.19	37.798
428	27 04	1.36	0.19	44.089
429	27.04	1.36	0.19	40.629
430	27.04	1.36	0.19	75.552
431	27.04	1.36	0 19	92 507
432	27.04	1.36	0.19	350.97
433	27.04	1 36	0.19	335.119
434	27.04	1.36	0 19	309.823
435	27.04	1.36	0.19	327.999
436	40.56	1.83	2.21	34.403
437	40.56	1.83	2 21	34.125
438	40.56	1.83	2.21	84 66
439	40 56	1.83	2.21	351.997
440	40.56	1.83	2.21	39.571
441	40.56	1.83	2.21	21.973
442	40.56	1.83	2.21	135.118
443	40.56	1.83	2.21	159.263
444	40.56	1.83	2.21	171.164
445	40.56	1.83	2.21	76.476

446	40.56	1.83	2.21	179.977
447	40.56	1.83	2.21	5.959
448	40.56	1.83	2 21	39.799
449	40.56	1.83	2 21	51.107
450	40.56	1.83	2.21	72.602
451	40.56	1.83	2.21	94.947
452	40.56	1.83	2.21	88.603
453	40.56	1.83	2.21	311.39
454	40.56	1.83	2.21	317.894
455	40.56	1.83	2.21	344 157
456	40.56	1.83	2.21	6.586
457	40.56	1.83	2.21	27 999
458	40.56	1.83	2 21	18 514
459	40.56	1.83	2.21	6.428
460	40.56	1.83	2.21	13.221
461	40.56	1.83	2.21	23.151
462	40.56	1.83	2.21	12.206
463	40.56	1.83	2.21	29.342
464	40.56	1.83	2.21	41.112
465	40.56	1.83	2.21	56.615
466	40.56	1.83	2 21	35 475
467	40.56	1.83	2.21	9
468	40.56	1.83	2.21	29.14
469	40.56	1.83	2 21	15 457
470	40.56	1.83	2.21	26.067
471	40.56	1.83	2.21	60.288
472	40.56	1.83	2.21	30.68
473	40.56	1.83	2.21	60.907
474	40.56	1.83	2 21	71 101
475	40.56	1.83	2.21	70.34
476	45.35	8.63	5.31	40.039
477	45.35	8 63	5.31	49.225
478	45.35	8.63	5.31	42.22
479	45.35	8.63	5.31	26.86
480	45.35	8.63	5.31	19.994
481	45.35	8.63	5.31	22.351
482	45.35	8.63	5.31	16.08
483	45.35	8.63	5.31	15.868
485	45.35	8.63	5.31	20.227
486	45.35	8.63	5.31	9.361
487	45.35	8.63	5.31	4.412
488	45.35	8.63	5.31	82.523
489	45 35	8 63	5.31	52.58
489	45.35	8.63	5.31	3.383
490	45.35	8.63	5.31	9.633
491	45.35	8.63	5.31	11.822
492	45.35	8 63	5.31	24.102
493	45.35	8.63	5 31	5.731
494	45.35	8.63	5.31	12.232
495	45.35	8.63	5.31	10 824

Table: Transportation Attributes

BUET ID	CBD ACC	M RD ACC	EDU_ACC	SHOP_ACC	W_MAR_AC
1	2551.767	735.514	1076.93	2537.897	2052.035
2	2433.072	854.209	687.52	2419.202	1933.34
3	2263 333	949.847	47.69	2249.464	1763.602
4	1838.9	1374.281	1200.01	1825.03	1339.168
5	1340.949	1305.074	714.36	1327.079	841.218
6	1701.277	862.384	1096.35	1366.848	1201.547
7	1578.52	682.779	507.09	1187.243	1078.789
8	1835.122	586.677	1059.72	1416.778	1335.392
9	2107.685	859.24	395.5	1689.341	1607.955
10	2286.905	902.176	192.49	1868 561	1787.175
11	2586.183	1082.035	1174.37	2167.839	2086.453
12	2520.816	697.195	21.91	2102.472	2021 086
13	2692.145	521.036	599.86	2278.632	2192.414
14	2886.845	326.336	1238.64	2465.42	2387.114
15	2887.276	301.805	1431.16	2440.888	2387.546
16	2910.164	513.318	1315.14	2496.65	2410.433
17	2731.057	621.003	727.52	2317.543	2231.326
18	2736.474	550.807	471.53	2722 604	2236 743
19	2132.799	1125.864	1318.16	2118.929	1633.068
20	2279.564	909.517	168.4	1861.22	1779 834
21	2801.964	411 217	960.16	2388 451	2302.233
22	2408.316	904.168	590.82	1989.972	1908.586
23	2772.95	416 131	1067 65	2354.606	2273.22
25	2094.432	845.987	1655.04	1676.088	1594.702
26	570.721	570.534	2087.55	505.228	570.534
27	530.18	529.994	1954 54	464.687	529.994
28	614.99	614.804	1636.54	549.497	614.804
29	780.072	779.885	1243.68	714 578	589.307
30	829 093	828.906	1404.51	763.599	638.328
31	567.845	567.658	192.4	506.315	376.294
32	688.831	688.644	2475.04	623.337	688.644
33	889.213	889.026	801.05	823.719	615.212
34	857.61	857.423	840.54	754.364	466.43
35	874.041	873.854	862.24	760.977	473.044
36	759 778	759 591	1970.47	671.974	759.591
37	866.758	866.571	2079.44	790.308	866 571
38	773.398	773.211	1914.18	707.904	773.211
39	945.724	937.276	1585 87	880.23	945.537
40	1040 277	861.086	1335.91	974.783	1040.09
41	1267.698	705.38	440.7	1197.513	990.892
42	1291.423	711.486	665.87	1203.618	1059.523
43	1085.105	757 919	997.43	997.3	1084 918
44	956.036	866.324	1302.18	868.232	955.85

45	835.221	835.034	1390.92	747.416	835.034
46	891.688	891.501	1513.3	803.884	891.501
47	770.878	770.691	2230 47	683.074	770.691
48	1060.237	919	1525.91	994.743	1060.05
49	1242.265	794.707	357.26	1176.772	965.459
50	1187.488	844 093	200.36	1121.994	910.681
51	248.847	249.033	445.64	336.651	249.033
52	278.758	278.945	308.55	366.563	278.945
53	317.802	317.989	418.68	405.606	317.989
54	418.438	418.624	124.61	506.242	418.624
55	292.603	292.79	353.98	380.408	292.79
56	225.202	225.389	592.96	313.007	225.389
57	401 28	401.467	710 53	489.085	401 467
58	378.006	378.193	634.17	465.811	378.193
59	461.345	461 532	494.86	549 15	461.532
60	348.576	348.389	1389	333.915	348.389
61	348.576	348.389	1389	333.915	348.389
62	320.284	320.471	699.7	408.089	320.471
63	409.735	409.549	1463.98	395.074	409.549
64	381.593	381.406	1497.33	366.932	381.406
65	349.183	348.996	1391	334.522	348.996
66	316.624	316.437	1434.61	396.735	316.437
67	344.494	344 307	1526 05	424.605	344.307
68	375.456	375.269	1627.63	455.567	375.269
69	372.86	372.673	1619.12	452 971	372.673
70	319.752	319 565	1444.88	399.863	319.565
72	663.28	663.093	69.05	569.943	471 627
73	463.356	463.169	867.08	544.022	270.553
74	433 213	433.026	766.37	513.325	239.855
75	207.501	207.314	1167.19	294.932	207.314
81	1188.109	328.628	735.46	224 877	513.761
82	1153.163	165.699	200.92	189.932	478.815
83	1186 528	199.063	310.38	223 296	512.179
84	1011.753	533.049	1039.04	317 335	121.901
85	979.09	576.352	1447.95	278.5	319.399
86	930.931	528.193	1289.95	230.341	336 828
87	871.314	528.488	1156.85	230 636	379.875
88	919 212	557.07	1140.84	259.218	291.381
89	914.942	612.856	1299 99	315.004	454 312
90	916.28	668.837	950 76	453.124	82.102
91	1007.802	728.533	1102.67	544.645	173.623
92	1064.044	711.025	1013 52	600.887	229.865
93	1069.745	648.403	839.78	606.588	235.566
94	1102.865	681.523	948.44	639.708	268.686
95	1114.676	628.956	775.98	651.519	280.498
96	1217.347	524.681	433.87	754.19	383.169
97	1274.815	477.661	279.61	811.658	440.636

98	1378.444	315.414	338.57	915 287	544.266
100	1513.967	217 078	783.19	914.805	679.788
101	777.254	777.068	656.68	864.685	720.908
102	816.336	816.149	784.91	903.767	759.99
103	801	800.813	734.59	888.43	744.654
104	871.636	871.449	558.64	959.066	871 449
105	885.515	885 328	1011.87	972.946	829.169
106	849.497	849.31	893.7	936.928	793.151
107	728.774	728.587	497.63	816.204	672.428
108	719.83	719.643	319.12	807.26	663.484
109	765.323	765.136	169 87	852.754	708 977
110	753.88	753.693	607.47	841.311	605.11
111	866.46	866.273	943.09	953 89	492.53
112	883.575	883.389	940.73	971 006	495.296
113	940.344	940.157	1219.23	1027.775	621.464
114	956.795	956.608	815 3	942.925	457.064
116	851.332	851.145	800.72	938.763	449.137
117	793.756	793.569	611.82	881.187	391.561
118	708.823	708.636	243.58	796.254	306.628
119	651 932	651.745	447.43	737.125	176.514
120	645.053	644.866	424.86	732.484	183.393
121	427.693	427.507	236.55	515.124	427.507
122	535.561	535.374	97.27	622.992	535.374
123	562.667	562.854	375.85	650.472	562.854
124	589.05	589.237	462.41	676.854	589 237
125	615.196	615.383	548 19	703.001	615.383
126	1718.064	367.028	1821 37	327.495	1717.877
127	1533.552	429.095	2025	389.562	1533.365
128	1468 078	654.335	2305.77	614 803	1467.892
129	1334.485	628.162	2108.41	588.629	1334.298
130	1478.416	706.743	2113 68	677.356	1478.229
131	1425.686	759.473	1940.69	730.086	1425.499
132	1374.884	798.005	1854.45	758.472	1374.697
133	1487.756	738.47	1826.71	738.47	1487.569
134	1501.289	690.521	1669.39	690.521	1501.102
135	1518.463	707.695	1725.74	707.695	1518.276
136	1364.876	774.062	984.83	774.062	1364.689
137	1423.961	727.632	1178.68	727.632	1423.774
138	2011.443	48.796	777.3	88.328	2011.256
139	2109.104	146 457	1097.71	185.99	2108.917
140	2181.826	219.18	1336.3	258.712	2181.639
141	2350 316	387.669	882.35	398.689	2350.129
142	2405.995	443.348	699.67	453.983	2405.808
143	2350.959	388.312	1187.74	427.845	2350.772
144	2374.253	411.606	1464.43	451.139	2374.066
145	2429.688	467.041	1570.42	506.573	2429.5
146	2506.344	543 697	1157.45	566.995	2506.157

147	2687.823	725.176	890.12	748.474	2687.636
148	2742.917	780.27	376.8	810.922	2742.729
149	2664.442	701.795	225.78	741 328	2664.255
150	2658.756	696.109	1252.26	735.642	2658.569
151	1193.131	1192.944	467.62	1280.562	1192.944
152	1205.545	1205.358	508.34	1292.976	1205.358
153	1122.062	1121.875	44.74	1209 493	1121.875
154	1271.015	1270.829	723.14	1358.446	1270.829
155	953.238	953 051	507.45	1040.669	953.051
156	1118.393	1118.207	108.51	1205.824	1118.207
157	1180.481	1180.294	208 53	1267.912	1149.139
158	1109.31	1109.123	442.03	1196.741	1077.968
159	1153.895	1153.708	295.75	1241.326	1122.553
160	1094.753	1094.566	489.79	1182.184	1063.411
161	1061.172	1060.985	642 79	1148.603	1060.985
162	1051.296	1051.109	632.37	1138.726	1019.953
163	1123.452	1123.265	521.35	1210 883	1037.434
164	1100.592	1100.405	596.34	1188.023	1014.575
165	1246.439	1246.252	645.96	1333.87	1158.329
166	1326.044	1325.857	907.13	1413.474	1237 933
167	1327.977	1327.79	1022.74	1415.408	1299.825
168	1360.981	1360.794	1021.75	1448.412	1272.871
169	1385.999	1385.812	1103 83	1473.43	1297.889
170	1272 3	1272 113	518.2	1359.731	874.748
171	1268.877	1268.69	739.17	1356 308	921.453
172	1360.056	1359.869	828.85	1447.486	1012.631
173	1214.897	1214.71	758.5	1302.328	867.829
174	1162.893	1162.706	951.51	1250.323	815.468
175	1033.936	1033.75	1305.9	1121.367	829.898
176	1763.232	1260.359	463.66	1850.663	1714.068
177	1988.883	1167.899	257.23	2076.314	1904.508
178	1885.272	1274.616	607.36	1972 703	1797 791
179	2000.474	1197 592	768.92	2087.905	1800.887
180	2083.001	1115.065	498.17	2170.432	1883.414
181	2305.977	1220.416	757.06	2342 888	1857.027
183	2140.13	1146.836	515.65	2126.26	1640.398
184	1961.463	1321.328	1088.13	1947.593	1461 732
185	2225.446	1300.948	1021.27	2312.877	1913.206
186	1771.762	1433.359	454.74	1757.892	1272.031
187	1860.902	1522.5	246.51	1847.032	1361.171
188	1984.629	1513.581	349.31	1970.759	1484.898
189	2019.485	1396.644	732.96	2087.696	1601.835
190	1788.887	1391.855	895.07	1876.318	1700.777
191	1627.715	1526.2	911.77	1715.146	1536.382
192	1804.873	1519.622	368.81	1892.304	1495.186
193	1847.247	1576.009	165.88	1900.541	1414.68
194	1863.153	1476.442	177.61	1950.584	1543.322

195	2083.628	1429.043	674.11	2069.758	1583.897
196	1850.528	1353.88	340.7	1937.959	1850.341
197	1866.363	1369.714	168.42	1953 794	1866 176
198	1853.968	1357.32	127.76	1941.399	1853.781
199	1879.078	1382.429	210.14	1966.509	1878 891
201	2032.949	1077 25	198.35	2120.381	1995.157
202	2251.54	869.013	447.25	2338.971	2174.249
203	2304.976	893.09	673.17	2392.407	2105.389
204	2247.796	1023.122	914.82	2335 227	2048.208
205	2277.893	1061.715	1013.56	2365.324	2051.516
206	2377.352	962.256	1078.37	2464.782	2150 974
207	2468.832	1030.274	1301.52	2556.263	2242.454
208	2482.431	818.272	517.85	2569.862	2321.821
209	2522.581	732.391	65.85	2610.012	2400.507
210	2752.946	574.057	784.28	2840 377	2514.723
211	2654.86	786.255	1244	2640.99	2155.128
212	2485.075	802.206	858.13	2471.205	1985 344
213	2229.56	1093.218	339.74	2215.69	1729.829
214	2243.357	866.843	420.41	2330.788	2205.564
215	2678.516	412.189	468.16	2765.947	2586.29
216	2743.703	273.524	682.02	2831.134	2743.517
217	2852.164	447.534	1019 01	2939 595	2613 941
218	3012 908	567.09	524.95	3025.708	2539.847
219	2892.856	420.367	43.58	2878.987	2393 125
220	3008.553	278.728	164.86	2994.683	2508.822
221	2464.853	559.641	741.31	2552.284	2464.666
222	2674.505	471.46	662.61	2761.936	2552.432
223	2404.682	639.343	721.55	2492.112	2404.495
224	2142 491	913.018	503.21	2229.922	2142.305
226	5057.159	2114.793	2583.79	5144.589	4902 343
227	5142.809	2200.443	2302.78	5230.24	4987.994
228	4997 103	2054.738	2428.66	5084.534	4842.288
229	4687.419	1745.054	1500.26	4774.85	4532.604
230	4753.971	1819.305	669.92	4841.402	4606.854
231	4510.643	1568.277	320 29	4598.073	4355.827
232	4422.705	1480.339	631.78	4510.135	4267 889
233	4397.649	1455.283	31 93	4485.08	4242.833
234	4262.11	1319.745	843 41	4349.541	4107.294
235	4906.245	1963.88	2130.57	4993.676	4751.43
236	4252.789	1310.423	894.05	4340.22	4097.974
237	3760.284	961.722	1082.97	3847.715	3749.272
238	4160.267	1460.15	1370.79	4247.697	4160.08
239	3865.649	923.284	232.17	3953.08	3710.834
240	3736.655	794.29	816.67	3824.086	3581.84
241	3550.056	607.69	1011.41	3637.486	3395.24
242	3345.571	403.205	814.45	3433.001	3190.755
243	3338.118	419 545	1159.24	3425.549	3207 095

244	3008.938	188.231	1014.11	3096.369	2975.78
245	3652.656	734.083	592.35	3740 087	3521 633
246	3686.229	743.864	710.35	3773.66	3531.414
247	4377.146	1434.78	35.34	4464.576	4222.33
248	4314.408	1372.042	1096.21	4401.839	4159.592
249	3983.468	1041.103	1156.71	4070.899	3828.653
250	4018.51	1076.145	1246.96	4105.941	3863.695
251	1672.329	206.927	766.97	1083.344	1172.598
253	1711.99	352.132	897 09	1064.366	1212.259
254	1666.347	306.489	747.34	1018.722	1166.616
255	1671.397	311.539	763.91	978.732	1171.666
256	1616.902	372.55	703.67	917.721	1117.171
257	1571.079	308.178	434.79	1079.051	1071.348
258	1542.671	336.586	341.58	1107.459	1042.94
259	1623 102	319.084	605 47	1089.957	1123.371
260	1664.155	360.137	740.15	1131.01	1164.424
261	1669.748	365.73	741.67	1136.603	1170.017
262	1676.634	372.616	719.08	1143.489	1176 903
263	1735.812	447 132	733.9	1218.005	1236.081
264	1776.473	487.793	867.3	1258.666	1276.742
265	1602.863	501.047	297.72	1211.586	1103.132
266	1583.945	512.528	235.65	1192.668	1084.214
267	1443.832	435.424	335.09	1042.776	944 101
268	1436 296	454.046	312.92	1035.239	936.565
269	1408.277	531.715	21.73	1007.22	908.546
270	1378.554	500.702	123.48	977.498	878.823
271	1333.571	565 184	234.84	942.294	833.84
272	1434.1	658.368	286.25	1042.823	934 369
273	1470 496	694.764	405.66	1079.219	970 765
274	1455.095	655.78	277 76	1063.818	955.364
275	1561.201	665.46	450.28	1169.924	1061.471
276	1109.851	912.327	796.89	719.096	610.12
277	1116.652	847.441	837.98	654.21	619.479
278	1112.234	828 408	341.45	649.792	615.06
279	1071.658	894.124	1057.05	609.215	574.484
280	1010 02	845.43	913.11	547.578	512.846
281	1007.117	842.527	903.58	544.675	509.943
282	1010.345	845.755	914.18	547.903	513.172
283	1125.967	961.377	1293.51	663.525	628 793
284	1123.991	959.401	1287.03	661.549	626.817
285	982.893	818.303	824.11	520.451	485.719
286	964.541	412.462	954 77	114.61	485.632
287	929.586	447.417	910.1	149.565	520.587
288	926.176	478.77	898.91	180 918	548.703
289	948.054	592.933	970.69	295.081	570.581
290	921.492	566.371	883.55	268.519	544.019
291	859.285	517.718	679.45	219.866	481.812

292	919.33	754.74	615.57	456.888	422.156
293	1087.891	881.927	724.84	688.696	588.161
294	1113 163	843.952	849.43	650.721	615.989
295	1151.692	788.95	711.99	689.25	654.518
296	1234 75	705.892	439.49	772.308	737.576
297	1061.908	982.379	995.13	717.577	562 177
298	958.108	911.628	682.71	613.776	458 377
299	1153.231	914.842	1125.02	690 789	656.057
300	1176.795	763.847	629.63	714.353	679.621
301	4946.092	2245.976	195.77	5033.522	4945.905
302	5040 109	2339.993	339.05	5127.54	5039.922
303	5041.188	2341.071	116.22	5128.618	5041.001
304	5132.379	2432.263	415.41	5219.81	5132.192
305	5078.012	2377.896	794.95	5165.443	5077.826
306	4963 961	2263.844	1169.13	5051.392	4963.774
307	5332.11	2599.938	642.16	5419.541	5331 923
308	5359.259	2627.088	553.09	5446.69	5359.073
309	5450.116	2717.944	255	5537.546	5449.929
310	5395 838	2663.667	574.17	5483.269	5395 652
311	5469.807	2737.635	816.85	5557.237	5469.62
312	5505.279	2773.107	137.26	5592.709	5505.092
313	5603.634	2871 462	248.67	5691.064	5603.447
314	5206.513	2474.341	942.62	5293.943	5206.326
315	5043.645	2311.473	1476.97	5131.075	5043.458
316	5080 713	2348.542	1355.35	5168.144	5080.526
317	4803.104	2070.932	860.46	4890.534	4802.917
318	4759.939	2050.334	718.85	4847.37	4759 752
319	4718.856	2009.252	584.06	4806.287	4718 67
320	4666 103	1956.498	410.99	4753.534	4665.917
321	4598 418	1888.814	3 09	4685.849	4598.232
322	4627.773	1918.168	285.23	4715 204	4627.586
323	4580.585	1870.98	246.75	4668.016	4580.399
324	4502.47	1792.865	9.54	4589.9	4502.283
325	4537.493	1827.888	105.37	4624.923	4537.306
326	2683.288	690.233	280.41	1678.37	1939.386
327	2719.221	726.165	398.29	1714.302	1975.318
328	2746.769	753.713	488.67	1741.85	2002.866
329	2671.749	372.743	1475.3	1708.517	1997.401
330	2693.265	394.259	1545.89	1730.034	2018 917
331	2589.046	290.04	1203.97	1625.814	1914.697
332	2619.239	320.233	1303.03	1656.007	1944.891
333	2898 694	599.688	735.88	1919.665	2180.681
334	2914.089	615.084	844.54	1950.858	2213 801
336	2914.158	615.152	953.21	1950.926	2239.81
337	2948.039	649.033	995.11	1984.807	2259.697
338	2907.272	608.267	1153.04	1944.041	2232.924
339	3226.848	927.843	825.25	2263.617	2552.5

340	3341.907	1120.39	747.61	2336.989	2598.005
341	3245.623	946.617	763.65	2282.391	2571.274
342	3338.465	1039.459	56.26	2375.233	2639.844
343	3323.717	1024.711	7.88	2360.485	2649.369
344	3310 811	1089 294	645.58	2305.892	2566.908
345	3535.671	1236.666	445.51	2572.44	2855.49
346	3565.037	1271.021	332.8	2560.118	2821.135
347	3595.137	1359.298	431.55	2590.219	2851.235
348	3584.663	1348 825	397 19	2579.745	2840.761
349	3702.862	1463.7	784.98	2697.944	2958.96
350	3692.975	1453.814	752.54	2688.057	2949.073
351	1730.104	175.014	1492.3	872.741	895.925
352	1806.817	251.727	1552.15	949.454	972.639
353	1745.009	242.439	1320.33	940.165	963.35
354	1726.592	260.855	1259.91	958.582	981.767
356	1602.432	284.339	780.02	982.065	986 216
357	1427.23	459.54	510.7	1157.267	1070 036
358	1509.031	417.148	488.02	1114.874	1068.303
359	1450.241	654.267	750 98	1158.898	1249.281
360	1337.598	662 797	778.96	1125.829	1168.576
361	1392.752	644.529	719 03	1070.791	1229.883
362	1463.542	715.319	351.28	1000.001	1300.673
363	1381.958	657.313	760.97	1067.206	1242.667
364	1262.452	912.792	648.8	937.477	1262.265
365	1170.684	1079.59	1087.36	1040.057	1170 497
366	1219.439	965.218	820.8	981.093	1219 253
367	1170.684	1079.59	1087.36	1040.057	1170.497
368	1012 826	1012.639	1424.85	925.021	1012.639
369	1113.637	1113 45	1755.6	1025 832	1113.45
370	1287.807	1193.713	2062.83	1154.18	1287.62
371	1120.861	1120 674	1779.3	1033.056	1120.674
372	1025.131	1024.944	674.83	937.327	1024.944
373	1060.525	1060.338	324.37	999.917	1060.338
374	1038.826	1038.639	1228.08	951.021	1038.639
375	1035.793	1035.606	316 21	975.185	1035 606
376	3491.5	1664.73	124.65	2237.068	2547.361
377	3507.994	1681.224	178.76	2253.562	2563.855
378	3354.019	1572.893	842.13	1862.229	2409 88
379	3387.335	1606 209	405.44	2132.904	2443.196
380	3383.541	1602.415	393	2129.109	2439 402
381	3516.784	1690.015	207.6	2262.353	2572.646
382	3696.005	1760.485	666.55	2441.573	2751.866
383	3725.111	1789.591	762.04	2470.679	2780 972
384	3719 694	1784.175	744.27	2465.262	2775.555
385	3676.136	1849.367	730.41	2421.705	2731.998
386	3662.873	1836.103	686.89	2408.441	2718.734
387	3676 135	1849.366	730.41	2421.704	2731.997

388	3684 468	1857.698	757.74	2430.036	2740.329
389	3632.501	1744.724	587.25	2378.069	2688.362
390	3632.501	1744.724	587.25	2378.069	2688.362
391	3693.839	1867.07	788.49	2439.408	2749.7
392	3699.434	1872.664	806.84	2445.002	2755.295
393	3739.774	1913.004	939.19	2485.342	2795 635
394	3739.774	1913.004	939.19	2485.342	2795.635
395	3739.774	1913.004	939.19	2485.342	2795 635
396	3068.257	1275.555	1301.81	1399.762	2234.079
397	2993.053	1303.25	2187.28	1324.558	2158.875
398	2967.272	1277.469	2102.7	1298 777	2133.094
399	2906.668	1216.865	1903.86	1238.173	2072.49
400	3134.387	1360.929	1457.01	1465 891	2300 209
401	3192.927	1503.123	374.76	1524.431	2358.748
402	3202 227	1512 423	1005.27	1533.731	2368.048
403	3243.645	1553.841	1141.16	1575.15	2409.467
404	3076 189	1286 448	1266.07	1407.693	2242 01
405	2955.369	1265.566	2063.64	1286.874	2121.191
406	2941.755	1251.951	2018.98	1273.259	2107.577
407	3082.091	1308.633	1285.44	1413.595	2247.913
408	2940.163	1250.36	2013.75	1271.668	2105.985
409	3140.84	1451.036	303.87	1472.344	2306.661
410	2980.333	1290.529	2145.54	1311.837	2146 155
411	2430.519	820 492	825.53	725.79	1596.341
412	2367.107	819.572	822.51	662 379	1532.929
413	2314.157	755.956	613.8	609.428	1479.979
414	2302.819	744.618	576.6	598.09	1468.641
416	5364.513	768.886	521.56	4401.281	4665 117
417	5374.654	758.745	554.83	4411 422	4675.258
418	5364.659	768.741	522.04	4401.427	4665.263
419	5376.19	757.21	559.87	4412.958	4676 794
420	5318 16	815.24	369.48	4354.928	4618.764
421	5286.787	846.612	266.55	4323.555	4587.391
422	5251.498	881.902	150.78	4288.266	4552 102
423	5251.498	881.902	150.78	4288.266	4552.102
424	4449.096	688.262	981.32	3485.864	3749.7
425	4959.193	1174.206	787.94	3995.961	4259.797
426	4435.455	674.62	936.56	3472 223	3736.059
427	4445.965	685 13	971 04	3482.733	3746.569
428	4470.917	710.083	1052 91	3507.686	3771.521
429	4480.987	720.152	1085.94	3517 755	3781.591
430	4489.312	728.478	1113.26	3526.08	3789.916
431	4537.08	776.246	1269.98	3573.848	3837.684
432	5535.547	521.849	1332.05	4572.316	4836.152
433	5503.345	630.054	977.05	4540.113	4803.949
434	5499.928	486.229	1448 91	4536.697	4800.532
435	5404.574	728.825	652.99	4441.342	4705.178

436	2556.503	858.017	568.25	1593.271	1882 154
437	2571.604	873.117	617.79	1608.372	1897.255
438	2414.122	730.138	148.7	1450.891	1739.774
439	3172.537	873.531	2613.52	2209.305	2498.188
440	3361.226	1062.221	758.76	2397.995	2686.878
441	3345.083	1046.078	705.8	2381.852	2670.735
442	3062.468	763.463	209.66	2099.237	2388.12
443	2982.146	683.14	587.51	2018.914	2307.797
444	2996.887	697.881	635.88	2033.655	2322.539
445	2899.169	600.163	1716.64	1935.937	2224.821
446	3023.529	724.523	723.28	2060.297	2349.18
447	2872.141	573.136	78.89	1908.91	2197.793
448	2920.981	621.975	239.12	1957.749	2246 633
449	2939.042	640.036	298.38	1975.81	2264.694
450	2974.857	675.852	415.88	2011.625	2300.509
451	3001.892	702 887	504.58	2038.661	2327.544
452	2990.824	691.818	468.27	2027 592	2316.476
453	3086.007	787.001	2329.63	2122.775	2411.659
454	3098.094	799.088	2369.28	2134.862	2423.745
455	3200.054	901.048	2703.79	2236.823	2525.706
456	2002.756	340.373	891.24	962.436	1223.453
457	2232.004	321.046	1305.69	1268.772	1557.656
458	1967 378	304.995	1463.03	1004.146	1293.03
459	1967.465	305.081	1463.31	1004.233	1293.116
460	1951.015	288.632	1409.34	987.783	1276.667
461	1998.026	335.642	1563.58	1034.794	1323.677
462	2233.11	312.305	1277.02	1269.878	1558 761
463	2270.224	555 528	1206.16	1306.992	1595.876
464	2319 724	523.898	869.72	1243.888	1504.904
465	2343.563	628.868	1446.78	1380.331	1669.215
466	2225.35	405.73	1583.53	1262.118	1551.001
467	2197.481	355.569	1418.96	1234.249	1523.133
468	2175.288	377.762	1491.77	1212.056	1500.94
469	2183.7	369.35	1464.17	1220.468	1509.351
470	2215.037	395.417	1549.69	1251.805	1540 688
471	2305.428	467.276	1055.48	1300.509	1561.526
472	2206.513	346.537	1389.32	1243.281	1532.164
473	2313 026	659.915	423.47	1107.871	1368.887
474	2214.234	507.78	1215.81	1251.003	1539.886
475	2265.786	687.416	268.48	1060.63	1321.647
476	2933.254	874.543	1865.2	874.543	2724.387
477	2942.654	883.942	1834.36	883.942	2714.987
478	2971.381	912.67	2008.35	912 67	2768.021
479	2890.24	831.529	1742.15	831.529	2686.881
480	2863.977	805.266	1655.98	805.266	2660.617
481	3056.882	998.171	1966.85	998.171	2868.169
482	3078.037	1019.326	17775.6	1019.326	2783.781

483	2960.742	902.031	1864.09	902.031	2901.075
484	3074.023	1015.312	1174.53	1015.312	3073.836
485	3194.977	1136.266	836.64	1136.266	3194.79
486	3208.947	1150.236	882.47	1150.236	3208.76
487	3522.751	1464.04	1881.04	1464.04	3479.238
488	3395.652	1336.941	1556.88	1336.941	3352.138
489	3334.304	1275.593	1355.61	1275.593	3290 791
490	3298.665	1239.954	1238.69	1239 954	3255 152
491	3043.674	664.652	1037.59	1139.997	2209.495
492	3027.002	647.98	1596.64	1176.208	2192.823
493	2712.365	333.343	564.37	938.18	1878 186
494	2906.253	527.232	1200.49	1055.459	2072.074
495	3152.513	773.491	869 07	1248.836	2318.334

APPENDIX B

Appendix B

Table: Actual and predicted house rent

House_ID	Actual House Rent	Predicted Rent (Initial ANN model)	Predicted Rent (Best ANN Model)	Predicted Rent (Hedonic Pricing)
361	2000	2095.457	2139.558	2109.099
362	1500	2129.653	2243.425	2093.291
363	3000	2799.002	3420.819	2518.2
364	3500	2663.631	3371.545	2379.904
365	2500	2487.608	2111.354	2338.29
366	2000	1448.365	1616.816	1608.179
367	3000	2378.684	2404.431	2283.267
368	2800	2127.752	2476.738	2155.447
369	2500	2233.238	2604.8	2227.172
370	2200	1729.116	1815.628	1712.838
371	2000	1839.005	1876.987	1738.1
372	2500	2044.202	2094.515	1949.444
373	2700	2901.149	2793.303	2924 925
374	3000	2957.398	3269.689	2902.987
375	1200	1512.558	1594.539	1547.288
376	1800	2150 936	2145 229	2189.659
377	3200	2832.615	2765.376	2894.234
378	2000	2259.945	2392.595	2208.282
379	1500	2038 601	2064.716	1989.052
380	2800	3178.398	3485.036	3466.939
381	3300	3440.232	3547.105	3418.044
382	3000	3022.835	3115.296	3258.241
383	2100	2778.228	2564.641	2701 711
384	2300	2283.523	2373.757	2313.13
385	3200	3121.599	2920 644	3076 461
386	2800	2763.053	2912.314	2858.466
387	2600	3029.298	2904.222	2995.829
388	1300	2274.656	2293.22	2219.265
389	2400	2886 686	2881.055	2934.879
390	2500	2489.739	2067.958	2551.704
391	2800	1780.168	2051.816	1644.128
392	3000	2668.026	2491 595	2695.994
393	2900	2605.807	2435.427	2617.184
394	2600	3084.588	3041.957	3073 84
395	3100	2269.256	2012.87	2239.62
396	900	2375.491	2261.575	2368.881
397	1700	2507.433	2372.828	2520.523
398	2100	2207.188	2052.13	2195.316
399	2100	1999.829	1912.966	2002.563

400	1800	2373.27	2293.767	2394.417
401	2400	2063.809	2357 602	2180 329
402	1500	2552.052	2616.528	2597.553
403	2500	3628.202	3541 062	4318 291
404	2500	2128.727	2242.046	2081.895
405	3000	2460 094	2614.327	2590.495
406	2000	1458.702	1522.353	1470.174
407	500	1208.191	1115.424	1255.428
408	2000	2246.629	2565.931	2231.783
409	3000	2445.291	2044.794	2335 695
410	2000	2214.729	1834.137	2162.471
411	2500	2369.608	1615.782	2315.593
412	3500	3002.441	2681.189	2798.919
413	1200	1526.415	1136.011	1556.134
414	2000	1445.677	1646.073	2040.287
415	1000	860.8999	1130.615	1095.497
416	1500	1964.974	1869.585	2057.052
417	3000	1952.486	1936.649	1832.337
418	2000	2103 843	1952.698	2176.365
419	400	1256.939	1030.201	1353 469
420	1200	2203 496	1757.727	2105.866
421	1500	1808.95	1583 956	1786.49
422	2000	2806.95	2473.325	2767.461
423	2500	1795 193	1721 625	1781.435
424	3000	2228.165	2091.755	2194.886
425	2500	2600.213	2757.576	2651 33
426	1500	1887.565	1604.013	1881.173
427	1900	2315.399	1529.362	2364.676
428	2500	2230.608	2297.541	2191.734
429	1200	1658.447	1166.899	1623.72
430	800	1357 973	709 1577	1356 287
431	2600	2128.31	2249.957	2102 996
432	1500	1917.413	2400.191	1765.833
433	600	600.9938	892 1793	799 8159
434	600	516.1232	636.8037	532.0384
435	800	704.3817	761.4359	929.8795
436	600	383.49	522.9702	539.693
437	300	442 0874	530.0228	577.8313
438	1000	851.5492	919.4736	744.1374
439	3500	2773.722	2663.233	2721.083
440	1300	1205.558	1205.966	1173.009
441	1500	3413.033	1512.329	3491.488
442	2000	1982.788	1754.134	1855.096
443	1800	1624 371	1333.905	1534 142
444	1000	1338.228	1250.435	1694.689
445	1600	1569.588	1405.691	1775.168
446	2200	2800.508	3113.173	2753.328

447	2500	1518.363	1683.198	1553 939
448	1700	1301.982	1370.51	1397.471
449	800	910.5846	827.5762	955.6391
450	1500	1232.491	1350 578	1148.38
451	800	631.7795	916.1721	566 9257
452	1000	1117 987	1285.915	1090.998
453	1600	1236.153	1383.453	1241.536
454	2500	2150 32	2697.199	2310.931
455	1000	1200 577	1394.499	1205.451
456	1500	1223.109	1362.544	1209.643
457	1200	1094.713	1287.737	1164.278
458	2000	1599.828	1656.014	1624.586
459	3800	2788.399	3296.481	2776.608
460	1500	1339 93	1211.872	1547.835
461	1200	1273.842	1299.936	1451.346
462	1800	1489.317	1416.017	1395.255
463	1200	1429.319	1247.178	1681.05
464	2000	1734.042	1828.5	2028.451
465	1200	521 3929	764.2921	944.1941
466	2000	1802.129	1609.699	1905.977
467	3000	3299.787	2909.854	3267.702
468	2000	2101.537	1925.979	2184.423
469	1200	1013.92	1227 677	1383.543
470	2000	1830.635	1345.119	1779.39
471	1200	1276.154	969.1458	1226.763
472	900	997.6525	766.1116	815 5585
473	6000	3853.721	3388.567	3414.564
474	2000	1933.464	1794.641	1948 439
475	1500	1686.935	2022.746	1795.176
476	4400	2759.308	2785.064	2759.848
477	3000	2438.756	2459 633	2429.429
478	2000	2006.456	1761.449	1985.23
479	2500	2792.88	2694.929	2697.776