DECISION SUPPORT SYSTEM FOR AFFORDABLE HOUSING

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Abstract: This research used neural networks to develop a decision support system, and model the relationship between one's living environment and residential satisfaction. Residential satisfaction was investigated at two affordable housing multifamily rental properties located in Atlanta, Georgia. The neural network was trained using data from Defoors Ferry Manor and the network was validated using data from Moores Mill. The neural network accurately categorized ninety-eight percent of the cases in the training set and ninety-three percent of the cases in the validation test set. This research represents a first attempt to use neural networking to model the relationship between one's living environment and residential satisfaction.

1 INTRODUCTION

There are several challenges and complexities that are involved in managing affordable housing properties, including 1) social programming, 2) meeting financial goals, 3) budgeting, 4) compliance with governmental and local housing regulations, 5) decreasing tenant turnover and vacancy rates, and 6) maintaining the physical building structure. Once provided by government funded programs and for-profit developers, nonprofit organizations have more recently taken on the task of housing the nations' less privileged, lower-income households. Several studies have examined the organizational performance of nonprofit management properties. One of the most recent studies suggests several indicators for determining management performance; one of the indicators was residential satisfaction (Bratt et al. 1994).

Francescato, Weidemann, Anderson, and Chenoweth proposed that people's satisfaction with where they lived was sufficiently important in itself to merit examination (Francescato, Weidemann, Anderson and Chenoweth, 1974; 1979). Understanding the determinants of satisfaction became the focus of their study of 37 multifamily housing developments. They initially proposed a model that can be interpreted as focus ing on the affective response of residents to their housing environment. They conceived of satisfaction, or affection for the home, as being a function of different categories of variables: the objective characteristics of the residents (e.g., age, sex, previous housing experience), the objective characteristics of the housing environments, and the occupants' perceptions or beliefs about three aspects of their housing environment (e.g., the physical environment, the housing management, and the other residents). In conducting their study of the 37 sites, their objective was to determine predictors of residents' satisfaction.

Whereas Francescato, Weidemann, Anderson, and Chenoweth focus on the use of residential satisfaction as a criterion, Campbell, Converse, and Rodgers were interested in examining residents' satisfaction as a determinant of perceived quality of life (Campbell, Converse and Rodgers, 1976). Marans and his colleagues indicated the importance of including objective measures of the physical environment in a model of satisfaction (Marans and Rodgers, 1975).

As a result, Marans and Sprecklemeyer presented a conceptual model for use in the understanding of, and guiding research on, relationships between objective conditions, subjective experiences, and residential satisfaction (Marans and Spreckelmeyer, 1981). This model has also been used in conjunction with research on recreational environments and institutional settings. More extensive versions of this model are also in Marans' research (Marans, 1976; Marans and Rodgers, 1975).

Work at the Institute for Social Research, has been directed toward the degree of agreement

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between perceptions of the neighborhood and objective physical measures of the actual conditions around them (Marans, 1976). Similarly, Weidemann, Anderson, Butterfield, and O'Donnell all have examined the relationship between objective measures of attributes of homes, residents' perceptions and beliefs about those attributes, and residents' satisfaction with their home environments (Weidemann, Anderson, Butterfield and O' Donnell, 1982). As Rodgers and Converse, Craik and Zube, Hempel and Tucker, and Snider point out, both subjective and objective inputs are important, and neither can be properly interpreted in the absence of the other.

This research examines residential satisfaction not in a context of solving any social or behavioral problem, but to assist decision makers in the business community. Several techniques are traditionally used to address issues concerning residential satisfaction ranging from multivariate to regression analysis. This research develop a systematic approach to predict residential satisfaction by developing a neural network decision support system that can assist owners in making decisions that will meet their residents' needs.

2 BACKGROUND INFORMATION

Residential satisfaction was investigated at two affordable housing multifamily rental properties located in Atlanta, Georgia named Defoors Ferry Manor and Moores Mill. Nonprofit housing developers, Atlanta Mutual Housing Association (AMHA) and Atlanta Neighborhood Development Partnerships (ANDP), respectively owns Defoors Ferry Manor and Moores Mill.

This research used neural networks to develop the decision support system, and to model the relationship between one's living environment and residential satisfaction. A residential satisfaction questionnaire was mailed out to residents at both rental properties. Eighty residents from Moores Mill and ninety-nine from Defoors Ferry Manor responded to the questionnaire. The questionnaire solicited residents' responses in the following areas: 1) residents' demographic information, 2) rental history, rental behavior, rental intentions, residential satisfaction, and residents' perception of their property meeting their needs, 3) residents' feelings towards rehabilitation, 4) participation in community events, residential committees, and social services, 5) satisfaction with property management, 6) satisfaction with maintenance, 7) satisfaction with community, 8) satisfaction with housing structure, and 9) residents' feelings of safety and security.

3 RESEARCH APPROACH

The residential satisfaction decision support system presented is a multilayered feedforward neural network. The neural network is trained using Defoors train dataset. The data is divided into two groups: input variables and an output variable. The inputs are the independent research variables specified in the model; the output variable SATIS is the dependent variable. The train dataset is made up of data rows, which makes up a set of corresponding independent variables and a dependent variable. These data rows are also referred to as cases. The decision support system is developed by first training the neural network. Training a neural network refers to the process of the model "learning" the patterns in the training dataset in order to make classifications. The training dataset includes many sets of input variables and a corresponding output variable. When the value of an input variable is fed into an input neuron, the network begins by finding linear relationships between the input variables and the output variable. Weight values are assigned to the links between the input and output neurons; every link has a weight that indicates the strength of the connection. The weights of the network are set randomly when it is first being trained. After all the rows of Defoors' dataset are passed through the network, the answer the network is producing is repeatedly compared with correct answers, and each time the connecting weights are adjusted slightly in the direction of the correct answer. If the total of the errors of all cases in the dataset is too large, then a hidden neuron is added between the inputs and outputs. The training process is repeated until the average error is within an acceptable range. The errors between the network and the actual result are reduced as more hidden neurons are added. The network has learned the data sufficiently when it has reached an acceptable error and is ready to produce the desired results, which are called classifications, for all of the data rows. The effectiveness of neural networks is demonstrated when the trained network is able to produce good results for data that the network has never seen before. This is examined using the trained network on Moores Mill test dataset.

The neural network output variable is SATIS which describes residential satisfaction which indicates residents overall living satisfaction. This variable had four categories that respondents could select from to describe their satisfaction level:

1=very dissatisfied, 2=somewhat dissatisfied, 3=somewhat satisfied and 4=very satisfied. These categories were collapsed into two categories to simplify the neural network model: 1 & 2=NOT SATISFIED and 3 & 4=SATISIFIED. Thus, the residential satisfaction train dataset is clustered into 2 categories: NOT SATISFIED and SATISFIED. Table 1 and Table 2 provide definitions of the input variables that were used to train the neural network.

Table 1: Input data for neural network

Variable Name	Definition
SATPROMAN	How satisfied residents are with the property management staff.
TENANTPOLICIES	How satisfied residents are with property management's tenant selection policies.
RFAIRLY	How satisfied residents are with property management enforcing rules fairly.
TALK	How satisfied residents are with availability of property management staff to address residents' concerns.

4 NEURAL NETWORK ANALYSIS RESULTS

Table 3 below displays the network's progress during training. Number of hidden neurons trained displays the total number of hidden neurons that have been added while the net is learning. Training the net involves adding hidden neurons until the network is able to make good classifications. Optimal number of hidden neurons displays the number of hidden neurons that best solves the classification problem. Training time is the length of time it took for the network to learn before it was able to make accurate classifications.

Figure 1 shows the number of hidden neurons graphed against the percentage of correct classifications. The vertical line between the curve and the x-axis shows that the network needed 56 hidden neurons during training before it can make correct classifications on the dataset.

Table 2: Input data for neural network continued.

Variable Name	Definition
COOPERATIVE	How satisfied residents are with the ability of property management staff to cooperate with residents.
FRIENDLY	How satisfied residents are with property management level of friendliness towards residents.
RECOMMEND[1]	If residents will recommend their apartment complex to a friend as a place to live.
QUALLIFE[2]	Residents' quality of life after renovations.
BLDQUALITY	How satisfied residents are with the quality of the apartment buildings on the property.
REPAIRSQUALITY	How satisfied residents are with the quality of maintenance repairs.
CLEANNESS	How satisfied residents are with the overall cleanliness of the property.
COMMUNCLEAN	How satisfied residents are with the cleanliness of the community that surrounds the apartment complex..
SATCOM	How satisfied residents are with the community that surrounds the apartment complex.
SAFENIGHTHOOD[3]	How safe residents feel during the night in their neighborhood.
SATMAINTEN	How satisfied residents are with the property's maintenance staff.
SAFENIGHT[3]	How safe residents feel during the night at their apartment complex.
SATUNIT	How satisfied residents are with their apartment units.

[1]Category responses are 1=will recommend, 2=will not recommend, and 3=do not know.
[2]Category responses are 1=better off than before, 2=worse off than before, and 3=about the same as before.
[3]Category responses are 1=very unsafe, 2=somewhat unsafe, 3=somewhat safe, and 4=very safe.

Table 3: Network training information and parameters

# of input variables:	18
output variable:	SATIS
Number Of Hidden Neurons Trained:	79
Optimal Number Of Hidden Neurons:	56
Training time:	49'

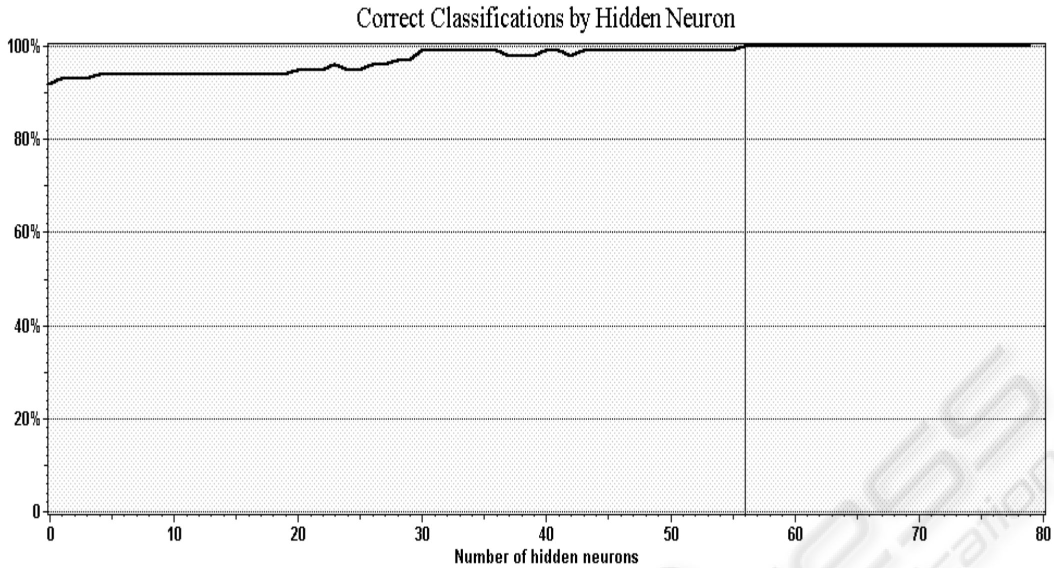

Figure 1: Graphical display of correct classifications by number of hidden neurons

4.1 Actual and Predicted Outputs

Tables 4, 5, and 6 display the actual and classified outputs for all the data rows in the trained dataset. This table displays results for every row in the data file to which the net was applied. The Row # column is the number of the row in the data file for each example. An asterisk is displayed beside the row number that the model makes an incorrect classification. The Actual column displays the category classification as it appears in the data file. The Classified column displays the category classification predicted by the network; the classification is either satisfied or not satisfied. The Not Satisf. and Satisf. columns are output classification categories and display the network's classification strength for each category. This value is the neuron activation strength for each category based on that set

of input values. This value can loosely be thought of as a probability; the values for all categories add up to 1. When the value is close to 1 in a category, the network is more confident that the example set of inputs belongs to that particular category. As shown in the Tables 4, 5, and 6 below, there were only 2 data rows (rows #15 & #64) that the network classified incorrectly. These two rows were classified as satisfied with a weight value of .998 (row #15) and .749 (row #64).

Table 4: Actual and classified outputs for all rows of trained data.

Row#	Actual	Classified	Not Satisf.	Satisf
1	satisf.	satisf.	0.000	1.000
2	satisf.	satisf.	0.003	0.997
3	not sa.	not sa.	0.999	0.001
4	not sa.	not sa.	0.995	0.005
5	satisf.	satisf.	0.000	1.000
6	satisf.	satisf.	0.000	1.000
7	satisf.	satisf.	0.000	1.000
8	not sa.	not sa.	0.992	0.008
9	not sa.	not sa.	0.997	0.003
10	satisf.	satisf.	0.000	1.000
11	satisf.	satisf.	0.000	1.000
12	satisf.	satisf.	0.000	1.000
13	not sa.	not sa.	0.999	0.001
14	satisf.	satisf.	0.000	1.000
15 *	not sa.	satisf.	0.002	0.998
16	satisf.	satisf.	0.002	0.998
17	satisf.	satisf.	0.000	1.000
18	satisf.	satisf.	0.000	1.000
19	satisf.	satisf.	0.000	1.000
20	satisf.	satisf.	0.000	1.000
21	not sa.	not sa.	0.999	0.001
22	satisf.	satisf.	0.000	1.000
23	satisf.	satisf.	0.000	1.000
24	satisf.	satisf.	0.004	0.996
25	not sa.	not sa.	0.999	0.001

*denotes a data row that was classified incorrectly

4.2 Agreement Matrix for Training Network

The agreement matrix shows how the network's classifications compare to the actual classification in the Defoors data file in which the network was applied. Table 7 is the agreement matrix for the trained networking using Defoors data file. Column labels Actual "NOT SATISFIED" and Actual "SATISFIED" refer to the category classification in the data file. The row labels Classified as "NOT SATISFIED" and Classified as "SATISFIED" refer to the network's predictions.

When the network was applied to 99 rows of training data, there were 22 actual examples of residents being "NOT SATISFIED", but the network classified 2 of those cases as "SATISFIED" and 20 as "NOT SATISFIED". There were 77 actual cases of residents being SATISFIED, which the network confirmed.

Table 5: Actual and classified outputs for all rows of trained data continued

Row#	Actual	Classified	Not Satisf.	Satisf
26	satisf.	satisf.	0.007	0.993
27	not sa.	not sa.	0.984	0.016
28	satisf.	satisf.	0.014	0.986
29	not sa.	not sa.	0.999	0.001
30	satisf.	satisf.	0.001	0.999
31	satisf.	satisf.	0.000	1.000
32	satisf.	satisf.	0.000	1.000
33	satisf.	satisf.	0.021	0.979
34	not sa.	not sa.	1.000	0.000
35	satisf.	satisf.	0.000	1.000
36	satisf.	satisf.	0.000	1.000
37	satisf.	satisf.	0.000	1.000
38	satisf.	satisf.	0.000	1.000
39	not sa.	not sa.	0.999	0.001
40	satisf.	satisf.	0.001	0.999
41	satisf.	satisf.	0.000	1.000
42	satisf.	satisf.	0.000	1.000
43	satisf.	satisf.	0.000	1.000
44	satisf.	satisf.	0.003	0.997
45	not sa.	not sa.	1.000	0.000
46	satisf.	satisf.	0.000	1.000
47	satisf.	satisf.	0.000	1.000
48	satisf.	satisf.	0.000	1.000
49	not sa.	not sa.	0.829	0.171
50	satisf.	satisf.	0.018	0.982
51	satisf.	satisf.	0.001	0.999
52	satisf.	satisf.	0.021	0.979
53	satisf.	satisf.	0.000	1.000
54	satisf.	satisf.	0.045	0.955
55	satisf.	satisf.	0.000	1.000
56	satisf.	satisf.	0.000	1.000
57	satisf.	satisf.	0.000	1.000
58	satisf.	satisf.	0.000	1.000
59	satisf.	satisf.	0.008	0.992
60	satisf.	satisf.	0.009	0.991
61	satisf.	satisf.	0.000	1.000
62	satisf.	satisf.	0.000	1.000
63	satisf.	satisf.	0.002	0.998
64 *	not sa.	satisf.	0.251	0.749
65	not sa.	not sa.	0.947	0.053
66	satisf.	satisf.	0.095	0.905
67	not sa.	not sa.	0.790	0.210
68	satisf.	satisf.	0.000	1.000
69	satisf.	satisf.	0.001	0.999
70	satisf.	satisf.	0.014	0.986
71	satisf.	satisf.	0.000	1.000
72	satisf.	satisf.	0.000	1.000
73	not sa.	not sa.	0.742	0.258
74	satisf.	satisf.	0.003	0.997
75	satisf.	satisf.	0.000	1.000

*denotes a data row that was classified incorrectly

Table 6: Actual and classified outputs for all rows of trained data continued.

Row#	Actual	Classified	Not Satisf.	Satisf
76	satisf.	satisf.	0.003	0.997
77	satisf.	satisf.	0.066	0.934
78	satisf.	satisf.	0.000	1.000
79	satisf.	satisf.	0.000	1.000
80	satisf.	satisf.	0.011	0.989
81	not sa.	not sa.	1.000	0.000
82	not sa.	not sa.	1.000	0.000
83	not sa.	not sa.	0.996	0.004
84	not sa.	not sa.	0.944	0.056
85	satisf.	satisf.	0.000	1.000
86	satisf.	satisf.	0.001	0.999
87	satisf.	satisf.	0.000	1.000
88	satisf.	satisf.	0.000	1.000
89	satisf.	satisf.	0.001	0.999
90	satisf.	satisf.	0.000	1.000
91	satisf.	satisf.	0.000	1.000
92	satisf.	satisf.	0.001	0.999
93	satisf.	satisf.	0.000	1.000
94	satisf.	satisf.	0.000	1.000
95	satisf.	satisf.	0.000	1.000
96	satisf.	satisf.	0.000	1.000
97	satisf.	satisf.	0.016	0.984
98	satisf.	satisf.	0.000	1.000
99	satisf.	satisf.	0.087	0.913

4.2.1 Explanation of Classifier Statistical Parameters

There are statistical parameters that are specific to the classifier. They reflect the neural network performance compared to the actual classification. These parameters apply to each output classification (SATISFIED and NOT SATISFIED) separately.

The following classification parameters are calculated from the comparison of the actual and neural network classification. The neural network classification can be considered as the predicted classification from the network. The actual classification can be considered as the true classification, which comes from the Defoors train database. Below is an explanation for the classifier parameters for *ACTUAL SATISFIED* cases**.** When the category is *ACTUAL NOT SATISFIED*, the terms are reversed.

True-Positive Ratio (also known as Sensitivity): is equal to the number of residents *classified as SATISFIED* by the network that were *actually confirmed to be SATISFIED* (77) through the Defoors train dataset, divided by the *total number of SATISFIED* (77) residents as confirmed by the Defoors train dataset. It is also equal to one minus the *False-Negative ratio*. 77/77=1.00

False-Positive Ratio: is equal to the number of residents *classified as SATISFIED* by the network that were *actually confirmed to be NOT SATISFIED* (2) by the Defoors train dataset, divided by the *total number of NOT SATISFIED* (22) residents as confirmed by the Defoors train dataset**.** It is also equal to one minus the *True-Negative ratio***.** 2/22=0.09

True-Negative Ratio (also known as Specificity): is equal to the number of residents *classified as "NOT SATISFIED"* by the network that were *actually confirmed to be "NOT SATISFIED"* (20) by the Defoors train dataset, divided by *the total number of "NOT SATISFIED"* (22) residents as confirmed by the Defoors train dataset. It is also equal to one minus the *False-Positive ratio***.** 20/22=0.91

False-Negative Ratio: is equal to the number of residents *classified as "NOT SATISFIED"* by the network that were *actually confirmed to be "SATISFIED"* (0) by the Defoors train dataset**,** divided by *the total number of "SATISFIED"* (77) residents as confirmed by the Defoors train dataset. It is also equal to one minus the *True-Positive ratio***.** 0/77=0.00

Sensitivity and Specificity: The terms sensitivity and specificity come from medical literature, but are now being used for neural network classification problems. Sensitivity and specificity are calculated by comparing the network's results with the 99 rows of training data for all possible output categories (SATISFIED and NOT SATISFIED).

Sensitivity is a concept that can be thought of as the probability that the mode will detect the condition when it is present. Sensitivity (true positives) equals 1 minus the number of false negatives. Examining the column labeled *Actual SATISFIED*:

*Sensitivity (true positives)***:** is equal to the number of residents the network *classifies as SATISFIED* that are also confirmed as *SATISFIED* by the Defoors train dataset (77) divided by the total number of residents confirmed as *SATISFIED* by the Defoors train dataset (77). 77/77=1.00 or 100%. This number implies that the sensitivity of the model for satisfaction is 100.00%. Specificity is a concept that can be thought of as the probability that the network model will detect the absence of a condition. Specificity (true negatives) equals 1 minus the number of false-positives. Examining the column labeled "actual satisfied":

Specificity (true negatives): equals the number of residents the network *classifies as NOT SATISFIED* that are also confirmed by the Defoors train dataset as *NOT SATISFIED* (20) divided by the total number of residents confirmed as *NOT SATISFIED* by the Defoors train dataset (22). 20/22=.9091 or 90.91%. This number implies that the specificity of the model for the model is 90.91%.

The calculations above for sensitivity and specificity were for the category *Actual SATISFIED***.** When the category is *Actual NOT SATISFIED*, the terms are reversed.

Table 7: Agreement matrix for trained network using Defoors data file

	ACTUAL "NOT SATISFIED"	*ACTUAL "SATISFIED"*	*TOTAL*
Classified as "NOT SATISFIED"	20	0	20
Classified as "SATISFIED"	2	77	79
TOTAL	22	77	99
True-Positive Ratio	0.91	1.00	
False-Positive Ratio	0.00	0.09	
True-Negative Ratio	1.00	0.90	
False-Negative Ratio	0.09	0.00	
Sensitivity	90.91%	100.00%	
Specificity	100.00%	90. 91%	

4.2.2 ROC (Receiver Operating Characteristic Or Relative Operating Characteristic) Curve Graphs For Trained Network

The ROC graphs the false-positive ratio on the x-axis and the true-positive ratio on the y-axis for each classification category. The circle plotted on the curve shows the intersection of the true-positive and the false-positive ratio on the y-axis for each classification category, and converts continuous probabilities to binary classifications for the trained network.

The area under the curve represents how well the network is performing. A value close to 1 means that the network is discriminating very well between the different output categories. The area under ROC curves shown in Figure 2 and Figure 3 below for both, NOT SATISFIED and SATISIED categories, is .9740 which implies that there is a 97.40% chance that the network will make correct classifications.

5 VALIDATION OF NEURAL NETWORK

After the residential satisfaction decision support system was trained using data from Defoors train dataset, the model was validated by running the model on Moores Mill test data and observing how efficient the model was in discriminating between different output categories (NOT SATISFIED and SATISFIED). The Moores Mill test dataset has the same input variables and output variable as the train dataset. There are 80 data rows in the Moores Mill train dataset. Out of the 80 data rows, 70 residents were SATISFIED; 10 were NOT SATISFIED. This section will present similar model validation statistical information that was presented on training the network model.

5.1 Actual and Predicted Outputs

Tables 8-10 display the actual and classified outputs for all the data rows in the test dataset. As shown in these three tables, there were 4 rows that were classified incorrectly: row numbers 25, 30, 46, and 63. All of these data rows were actually NOT SATISFIED, but the network classified them as SATISFIED. The weights that were assigned to these rows for the SATISFIED classification were respectively, 1.000, 0.814, 0.989, and 0.913.

Table 8: Actual and classified output for all of test data

Row#	Actual	Classified	Not Satisf.	Satisf
1	SATISF.	SATISF	0.004	0.996
2	NOT SA.	NOT SA.	0.905	0.095
3	SATISF.	SATISF.	0.005	0.995
4	SATISF.	SATISF.	0.000	1.000
5	SATISF.	SATISF.	0.000	1.000
6	SATISF.	SATISF.	0.003	0.997
7	SATISF.	SATISF.	0.000	1.000
8	SATISF.	SATISF.	0.004	0.996
9	SATISF.	SATISF.	0.000	1.000
10	SATISF.	SATISF.	0.001	0.999
11	SATISF.	SATISF.	0.000	1.000
12	SATISF.	SATISF.	0.256	0.744
13	SATISF.	SATISF.	0.000	1.000
14	SATISF.	SATISF.	0.000	1.000
15	SATISF.	SATISF.	0.079	0.921
16	SATISF.	SATISF.	0.000	1.000
17	SATISF.	SATISF.	0.002	0.998
18	SATISF.	SATISF.	0.000	1.000
19	SATISF.	SATISF.	0.000	1.000
20	NOT SA.	NOT SA.	0.590	0.410
21	NOT SA.	NOT SA.	0.990	0.010
22	SATISF.	SATISF.	0.000	1.000
23	NOT SA.	NOT SA.	0.997	0.003
24	SATISF.	SATISF.	0.001	0.999

Table 9: Actual and classified output for test data continued

Row#	Actual	Classified	Not Satisf.	Satisf
25 *	NOT SA.	SATISF.	0.000	1.000
26	SATISF.	SATISF.	0.000	1.000
27	SATISF.	SATISF.	0.000	1.000
28	SATISF.	SATISF.	0.000	1.000
29	SATISF.	SATISF.	0.000	1.000
30 *	NOT SA.	SATISF.	0.186	0.814
31	SATISF.	SATISF.	0.000	1.000
32	SATISF.	SATISF.	0.000	1.000
33	SATISF.	SATISF.	0.000	1.000
34	SATISF.	SATISF.	0.000	1.000
35	SATISF.	SATISF.	0.002	0.998
36	SATISF.	SATISF.	0.000	1.000
37	SATISF.	SATISF.	0.001	0.999
38	SATISF.	SATISF.	0.000	1.000
39	SATISF.	SATISF.	0.000	1.000
40	SATISF.	SATISF	0.079	0.921
41	SATISF.	SATISF.	0.001	0.999
42	SATISF.	SATISF.	0.003	0.997
43	SATISF.	SATISF.	0.107	0.893
44	SATISF.	SATISF.	0.001	0.999
45	SATISF.	SATISF.	0.000	1.000
46 *	NOT SA.	SATISF.	0.011	0.989
47	SATISF.	SATISF.	0.009	0.991

48	SATISF.	SATISF.	0.000	1.000
49	SATISF.	SATISF.	0.000	1.000
50	SATISF.	SATISF.	0.000	1.000
51	SATISF.	SATISF.	0.000	1.000
52	SATISF.	SATISF.	0.001	0.999
53	SATISF.	SATISF.	0.000	1.000
54	SATISF.	SATISF.	0.000	1.000
55	SATISF.	SATISF.	0.000	1.000
56	SATISF.	SATISF.	0.007	0.993
57	SATISF.	SATISF.	0.000	1.000
58	SATISF.	SATISF.	0.000	1.000
59	SATISF.	SATISF.	0.000	1.000
60	SATISF.	SATISF.	0.000	1.000
61	SATISF.	SATISF.	0.000	1.000
62	SATISF.	SATISF.	0.000	1.000
63 *	NOT SA.	SATISF.	0.079	0.921
64	SATISF.	SATISF.	0.000	1.000
65	SATISF.	SATISF.	0.000	1.000
66	SATISF.	SATISF.	0.000	1.000
67	SATISF.	SATISF.	0.000	1.000
68	SATISF.	SATISF.	0.000	1.000
69	SATISF.	SATISF.	0.002	0.998
70	SATISF.	SATISF.	0.141	0.859
71	SATISF.	SATISF.	0.000	1.000
72	SATISF.	SATISF.	0.000	1.000

*denotes a data row that was classified incorrectly

Table 10: Actual and classified output for test data continued

Row#	Actual	Classified	Not Satisf.	Satisf
73	SATISF.	SATISF.	0.001	0.999
74	SATISF.	SATISF.	0.012	0.988
75	NOT SA.	NOT SA	0.743	0.257
76	SATISF.	SATISF.	0.000	1.000
77	NOT SA.	NOT SA.	0.967	0.033
78	SATISF.	SATISF.	0.000	1.000
79	SATISF.	SATISF.	0.000	1.000
80	SATISF.	SATISF.	0.000	1.000

the network classified 4 of those cases as "SATISFIED" and 6 as "NOT SATISFIED". There were 70 actual cases of residents being "SATISFIED", which the network confirmed. A true-positive ratio of 1.00 and a false-positive ratio of .40 were given for the actual SATISFIED classification. The sensitivity which is also refer to as true positive is 100% which implies that there is a 100% chance that the network will detect when a resident is satisfied. On the other hand, the actual NOT SATISFIED classification has a true-positive ratio of .6 and a false- negative ratio of 0.0. The sensitivity for the actual NOT SATISFIED classification is 60% or .6 (false-positive), which means that there is a 60% probability that the computer will detect that the resident is not satisfied.

The ratio values and the percentages for sensitivity for Actual "Satisfied" and specificity for Actual "Not Satisfied" are the same for Tables 7 and 11. However, the network misclassified 4 data rows that were actually NOT SATISFIED but classified as SATISFIED which explains the 60% for specificity.

5.2 Network Agreement Matrix for Validating Network

Table 11 is the agreement matrix for validating the network model using Moores Mill data file. When the
network was applied to 80 rows of data, there were 10 actual cases of residents being "NOT SATISFIED", but

Table 11: Agreement matrix for validating network using Moores Mill data file.

	ACTUAL "NOT SATISFIED"	*ACTUAL "SATISFIED"*	*TOTAL*
Classified as "NOT SATISFIED"	6	0	6
Classified as "SATISFIED "	4	70	74
TOTAL	10	70	80
True-Positive Ratio	0.60	1.00	
False-Positive Ratio	0.00	0.40	
True-Negative Ratio	1.00	0.60	
False-Negative Ratio	0.40	0.00	
Sensitivity	60.00%	100.00%	
Specificity	100.00%	60.00%	

5.3 ROC for Validating Neural Network

Figure 4 and Figure 5 represent the ROC curves for the validation data for the network model. As mentioned in section 4.3, the circle plotted on the curve shows the intersection of the true-positive and the false-positive ratio on the y-axis for each classification category, and converts continuous probabilities to binary classifications for the trained network. The area under the curve represents how well the network is performing. A value close to 1 means that the network is discriminating very well between the different output categories. The area under the curves in Figure 4 and 5 is 0.9307. This implies that the overall effectiveness of the network is in discriminating between different output categories when validating the trained network is 93.07%.

6 CONCLUSIONS

As housing issues continue to grow as we move further into the 21st century, decision makers are faced with challenging decisions. Many of these decisions are made either through intuition, past experience, or ineffective traditional approaches. Making appropriate decisions commonly entails risk control and management. Although decision makers have some control over the levels of risks to which they are exposed, reduction of risk needs to be pursued by housing agencies to decrease costs and use resources efficiently. Housing policy makers are required, with increasing frequency, to subjectively weigh benefits against risks and assess associated uncertainties when making decisions. Such risk-based decisions require uncertainty modeling and analysis. Neural networks are mathematical models that emulate the processes people use to recognize patterns, learn tasks, solve problems, and address such uncertainty.

In conclusion, this research developed a residential satisfaction decision support system that can assist owners in making decisions that will meet their residents' needs. The system is based on neural networks. Residential satisfaction was investigated at two affordable housing multifamily rental properties located in Atlanta, Georgia named Defoors Ferry Manor and Moores Mill. Nonprofit housing developers, Atlanta Mutual Housing Association (AMHA) and Atlanta Neighborhood Development Partnerships (ANDP), respectively own Defoors Ferry Manor and Moores Mill

The neural network was trained using Defoors Ferry Manor data, and it took 49 seconds to train the network. Seventy-nine hidden neurons were trained. The neural network was applied to 99 data rows used to train the network. Ninety-seven of those rows were classified correctly and 2 rows were classified incorrectly. The ROC (Receiver Operating Characteristic) graph showed the efficiency of the network, and it was concluded that the network was 97.40% effective in making correct classifications.

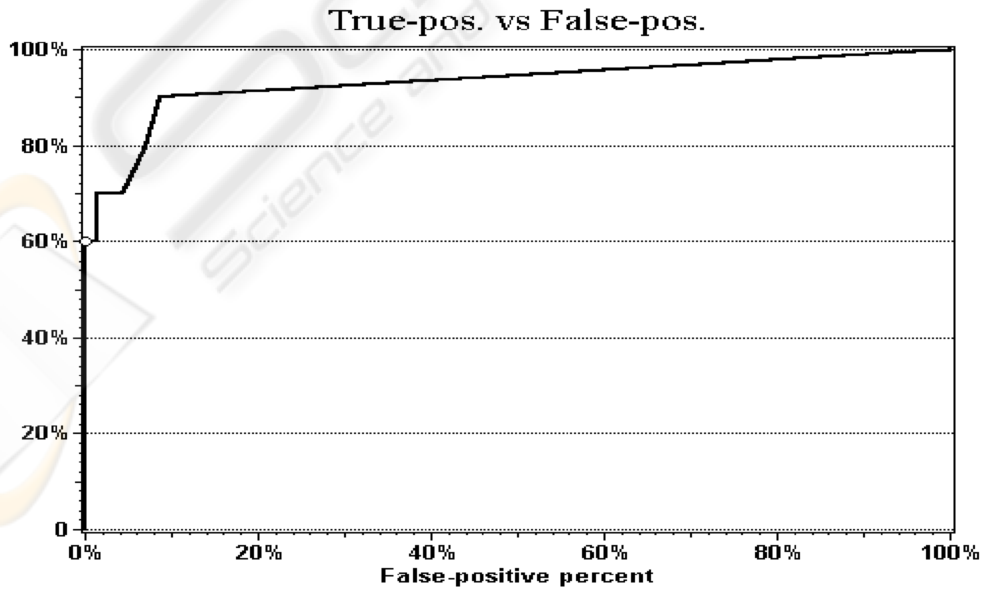

Figure 4: ROC for NOT SATISFIED classification test data.

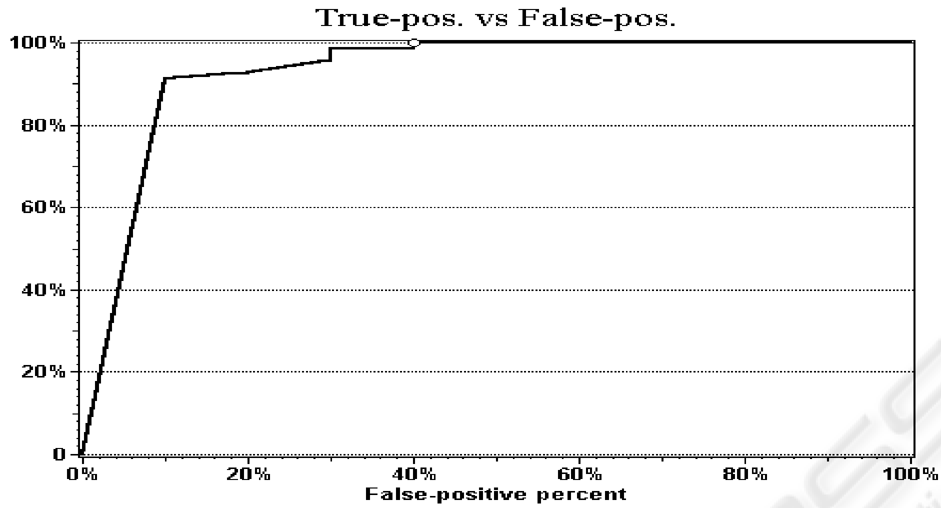

Figure 5: ROC for SATISFIED classification test set

The network was trained using data from Defoors trained data set; afterwards, the network was validated by running the network on Moores Mill test data and observing how efficient the network was in discriminating between different output categories. The Moores Mill test dataset has the same input variables and output variable as Defoors. There were 80 data rows in the Moores Mill train dataset. Out of the 80 data rows, 4 rows were classified incorrectly. When the network was applied to 80 rows of the data, there were 10 cases where residents were "NOT SATISFIED"; but the network classified 4 of those cases as "SATISFIED".

The statistics related to the network's performance were that there was a 100% chance that the network will correctly predict a resident is satisfied. On the other hand, the specificity of the network for the actual SATISFIED classification was 60%, which means that there is a 60% chance that the computer will detect when the resident is not satisfied. The network's overall effectiveness in discriminating between different output categories when validating the network was 93.07%.

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