

# Residential Property Value Modeling using the Group Methods of Data Handling-Neural Network and Regression Analysis: A Case Study of GHMC, India

Togiti Dilip<sup>1</sup>, M. Gopal Naik<sup>2</sup>, Aditya Mudigonda<sup>3</sup>

Submitted: 10/09/2022

Accepted: 20/12/2022

**Abstract:** location's demand and the purchasers' affordability determine the property's optimal value. To meet this optimal price the facilities in the properties are arranged through house sorting. Before sorting, it is important to find the significant facilities that contribute to the property value. The previous works mostly through qualitative assessment have identified the important factors influencing residential property value. The current article aims to determine the significant property facilities that are contributing to its value using statistical techniques. The facilities of a residential property considered in this study are Total Area, Age, Maintenance Cost, Number of bedrooms, Number of Toilet, Number of Balconies, facing of the property, Furnishing, Availability of Power Backup, Security, Elevator, Parking facilities. Data needed for the study were collected through a ground survey and interviews with the owners and real estate agents in the Greater Hyderabad Municipal Corporation (GHMC) Region. A total of 202 residential apartments that are yet to be sold were considered for the model development and 32 sold-out properties were obtained to validate the models. The significant facilities are identified using the p-test and the Group Methods of Data Handling- Neural Network (GMDH-NN) and linear regression techniques are adopted to develop the models for all possible combinations of the most significant factors. The accuracy of the developed models is assessed using  $R^2$  and Root Mean Square Error (RMSE) and Mean Average Percentage Error (MAPE). The study's findings indicate that the total area of the Residential apartment and the maintenance cost are the most significant factors. Both GMDH-NN and linear regression models developed using these factors show that the consideration of the Total area alone as a variable for prediction of property value has  $R^2 > 0.748$  and the RMSE and MAPE being less than 30%. The accuracy of prediction for the validation datasets using the Total area of the property as an input variable is more than 70% for both models. Identifying the significant factors using statistical techniques and then developing the models using these factors is the novelty of the research. the proposed models in the article can be used directly to understand the preferred facilities in Residential properties in the GHMC region and the adopted framework can be used for property valuation in general for any region

**Keywords:** Residential Property Value, Significant Property facilities, Group Methods of Data Handling- Neural Network (GMDH-NN), Linear Regression Analysis.

## 1. Introduction

Any entity under human utilization acquires a value. As more and more humans are moving into the cities in the search of employment and business opportunities, there is an unprecedented growth in the urban areas in the latter half of the 20<sup>th</sup> century. These urban and demographic changes have created immense demand for residential accommodation. The demand for a location and the affordability of the buyers will affix an optimized value to the property. The prediction of this price of a property is of prime importance to buyers, sellers, and Tax collecting agents. Generally, the property valuation is subjective in nature and is likely to impact the overall accuracy of the

prediction of the Property value (Joslin, 2005).

The real estate market is unique in that, every piece of property is different from every other. Each residential property is unique in its appeal to each prospective buyer. A final sale is arrived at through a series of price demands from the owners and the payable price of prospective buyers. The more people are willing to pay for a house or apartment at a particular location, the more housing services or higher will be the quality of the house. The same is achieved through house sorting. House sorting refers to the idea of trading-off between different facilities of a property so as to meet the demand of buyers and optimized value. Sorting is a bit tricky for the reason that the property can be arranged in as many ways as possible. During house sorting it is important for the planners and owners to keep in mind the significant facilities that a buyer is looking for and accordingly the changes can be made to the properties (Joslin, 2005) (Lenk et al., 1997).

The aim of the present study is to develop model for the computation of Residential Property value using the most significant facilities of Residential property.

The objectives of the present study are to,

<sup>1</sup>University College of Engineering, Osmania University, Hyderabad, Telangana- 500007.

Email: togitidilip@gmail.com

<sup>2</sup>University College of Engineering, Osmania University, Hyderabad, Telangana- 500007.

Email: mgnaike@osmania.ac.in

<sup>3</sup>University College of Engineering, Osmania University, Hyderabad, Telangana- 500007.

Email: aditya\_ouce@outlook.com

1. Identify the facilities that influence the Value of Residential Property
2. Identify the most significant facilities influencing the Value of Residential Property using statistical techniques.
3. Develop the GMDH-NN and Linear Regression based Model for the Prediction of the Residential Property Value using all possible combinations of the most significant factors.

## 2. Literature review

According to the hedonic model, the Property value is a function of structural characteristics, neighborhood characteristics and the location of the property within the market. Here the structural characteristics or property facilities are results of many direct and indirect influences. The purchasing power of the owner, his requirement of the facilities, and the available neighborhood amenities around it all contribute and optimizing the facilities and the price of a residential property.

Fisher and Martin (1994) discovered that the construction type, construction quality, architectural style, and other structural aspects all have a direct impact on the appearance of a structure. Although they are not directly related to consumption, they have an impact on the property's value since they affect its prestige. The superior quality of the structural elements and the additional elements affect the property price. Furthermore, the improvement in property quality is accompanied by an increase in maintenance costs.

According to Ustaolu (2003), the quality of construction components and the presence of certain interior services contribute value to the structure. At the same time, physical depreciation due to aging and wear affects the building's physical structure. Even if they are in a good location and are well-designed, older and worn-out properties do not generate the same income as new structures (Fisher & Martin, 1994)(Joslin, 2005)(Lenk et al., 1997). The impact of aging on property value was explored using qualitative assessment and regression analysis (Brandt & Maennig, 2011) (Janmaat, 2005). (Sirmans et al., 2006). According to the studies, the age of buildings is negatively connected with the value of residential properties. According to Grebler et al. (1956), the value of a property appears to fall by roughly 4% per year in the first few years of its life. On the other hand, their research demonstrates that the rate of depreciation decreases fast after then, becoming much lower in old age. Furthermore, it was shown that the property values in the Stoke-on-Trent postal area, England, fall by 0.26% per year of age (Fletcher et al., 2000). Ferlan et al., (2017) discovered in their survey that there is a negative relationship between the age and building value for averagely maintained residential properties, and statistical standard deviation shows that the values of residential properties in buildings older than 30 years were widely dispersed, indicating that respondents' estimates were quite different for properties aging beyond 30 years.

W. J. McCluskey et al., (2000) used the Ordnance Survey of Northern Ireland data to examine the effect of geography on residential property prices. Sale price, date of sale, age of property, Area, number of bedrooms and bathrooms, number of garages, kind of central heating, condition, neighborhood, and group cluster are the parameters they examined in their multiple regression model, calibrated by location adjustment factors. They discovered that location and structural features are the most important predictors of residential property values. Burinskien et al., (2011) also emphasized the importance of a property's status

and location, as well as its age, number of floors, and total useable area, on its property value. In their evaluation, Lenk et al. (1997) discovered that the number of bathrooms, bedrooms, age of the house, area of the property, and parking facilities all contributed favorably to the Residential Property value. Using a hedonic estimating method, Yayar and Deniz (2014) determined the factors influencing the value of apartments in Mersin's city center. The carpet area of the house, kitchen size, distance to the market, number of bathrooms, garage, central satellite system, private security, and elevator variables raise the price of housing; however, the fact that the house has a garden is on the site and is away from public transportation vehicles lowers the price of housing. According to Chau and Chin (2003), property components such as parking areas, heating systems, floor covering, wall covering, and woodwork work for doors and windows have a substantial influence on property value. Furthermore, the presence of a single garage adds a 6.9% disparity, while the presence of a double garage adds three times this amount; similarly, central heating adds roughly 6.5% to the price of a property. Ferlan et al. (2017) discovered through an expert study that the orientation or face of the property also related to the property value. Southwest and southeast are the most ideal orientations for residential houses in Slovenia, Europe, whereas north-east and north-west are the least favoured directions. Rodgers (1994) identified ventilation, attic, and fireplace as crucial considerations for a certain group of buyers in the adjustment process. According to hedonic regression analysis, the existence of an elevator in a building enhances the value of residential properties on higher floor levels, which is similar to the Hong Kong study (Choy et al., 2007). According to the findings, houses on higher levels with excellent views are more expensive and easier to sell. The study on the influence of balconies on the value of residential properties in Hong Kong discovered that balconies have a favourable effect on the value of a home, regardless of the quality of the view (Chau et al., 2004). The perspective from a floor or a building, on the other hand, is subjective and reliant on the economic, administrative, social, cultural, and environmental knowledge of the place and its surroundings. Aside from the issues listed above, power backup is critical for providing elevator and water supply services on an ongoing basis.

According to Selim (2009), the key factors influencing home prices were the kind of house, type of building, number of rooms, size of the house, and other structural characteristics. The outcomes of the hedonic model and the artificial neural network (ANN) were compared. It was discovered that the attributes derived from these studies lacked multiple linearity between the explanatory variables. Yilmazel et al., (2017) created 19 ANN-based models by varying the secret layer neuron counts, comparing the performances of these models, and determining the best appropriate secret layer neuron number. Even though the artificial Neural Network approach is very affordable and simple to implement, it requires larger data sets for model testing and validation. McGreal et al. (1998) assessed neural network model's capacity to predict the value of properties in Belfast, United Kingdom and concluded that the use of neural networks for assessment purposes remained difficult. The most likely reason is the neural network's 'black box' aspect, which does not provide insight into the interplay of the factors under consideration (W. McCluskey & Anand, 1999). (Rossini, 1997). In comparison to regular NN, Group methods for data handling (GMDH)- Neural

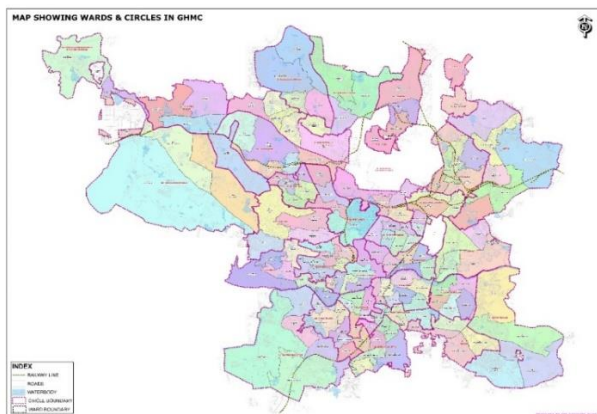
Networks were found to be even more accurate, and in a financial study where two approaches were used, GMDH-NN showed a 10-15% improvement (Pandya et al., 1999).

The earlier studies' analyses were primarily qualitative and limited to the identification of components and their relative weightage via a questionnaire survey. There is also a scarcity of research on the identification of significant factors using statistical techniques, which is addressed in the current work. After the most important elements have been identified, they are employed as input variables in the creation of residential property valuation models.

### 3. Study Area

Hyderabad, the capital and largest city of the Indian state of Telangana, is a multicultural and multi-nucleic city with a wide range of industries being part of the economy. The industrial revolution in the late 20<sup>th</sup> century and the Information technology revolution in the early 21<sup>st</sup> century completely changed the dynamics of the settlement in Hyderabad City.

To look into the needs and demands of the in-population and the migrating population, the Greater Hyderabad Municipal Corporation (GHMC) was formed. It is one of the largest municipal corporations in India extending over an area of 650 km<sup>2</sup>. The region under the control of GHMC is divided into 6 Zones which are further divided into 30 circles and 150 wards and is as shown in Figure 1. The responsibility of GHMC is to administer and provide basic amenities to the city. The body is also responsible for the property tax collection in the region. To accommodate the dynamic demographic changes the real estate and construction industry paced up keeping in view the growing and ever-changing needs of the inhabitants.



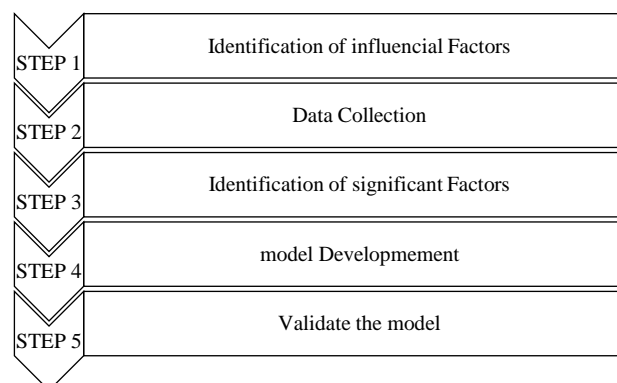
**Fig. 1.** Wards and Circle Map in GHMC

(Source: <https://www.ghmc.gov.in/Documents/NEW%20CIRCLES, WARDS%20MAP.jpg>)

In Hyderabad it was observed that inspite of the Covid-19 pandemic there is an upsurge in the demand and supply of the residential properties in the year 2021 as compared to that of year 2020. Further, for year 2021-22 it is observed that the share of the flats pricing between Rs 40 Lakhs to Rs 80 Lakhs holded nearly one third of the market followed by the window of Rs 80 Lakhs to Rs 1.5 Crore window. The growing needs and increasing dynamics of the residential properties shed light on the importance of the computation of the value of the residential properties and also the find the significant factors influencing the Value.

### 4. Methodology

The following are steps adopted for identification of the significant residential property facilities and the development of predictory model for residential property valuation in GHMC Region. The flowchart of the methodology adopted is as presented in figure 3.



**Fig. 3.** Flowchart of the methodology adopted.

#### **Step 1. Identification of the factors influencing the residential property value:**

As per the literature survey, the Property facilities that are found to directly or indirectly influence the property value are identified and are assessed in the current study.

#### **Step 2. Obtain the Property details**

The details of the residential Properties with respect to Property value and property facilities obtained in step 1 by conducting a ground survey and interview with the owners in the GHMC Region.

#### **Step 3. Conduct p-test to obtain the most significant factors**

P-test is a statistical test used for testing the hypothesis. In the P-test the probability of a measure to be out of a predefined significance level is measured. Typically, if p-value is below a confidence level of 95%, the null hypothesis is rejected and the alternate hypothesis is accepted. The software like Excel, R-Language, SPSS, Jamovi can directly compute the p-value.

In the current research, null hypothesis represents that, there is no relationship between the Residential property value and the property facilities. Lower the p value higher the significance of the factor. In present study if  $p < 0.001$  for a factor it is considered to be the most significant factors. and if  $p < 0.05$  they are moderately significant factor.

#### **Step 4. Develop model for the prediction of Residential Property value**

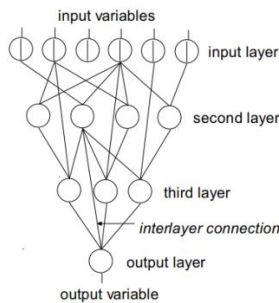
For all the possible combinations the significant factors obtained in step 3, Group methods for data handling (GMDH)- Neural Network and Linear regression models are developed using the facilities data of 202 residential properties to be sold out as input.

#### **Group method of Data Handling (GMDH)- Neural Network**

Group methods of Dara Handling (GMDH) is a set of inductive techniques for computer-based mathematical modelling of multi-parametric datasets, including completely automatic structural and parametric model optimization. Data mining, knowledge discovery, prediction, complex systems modelling, optimization, and pattern recognition are all applications of GMDH. GMDH algorithms are distinguished by an inductive method that sorts out difficult polynomial models and selects the best solution using an

external criterion. The inductive nature of neural networks and GMDH algorithms has prompted researchers to investigate areas where these two concepts could mix.

Ivakhnenko proposed a combined method in the early 1990s that replaced the passive neurons of GMDH algorithms with the active neurons of neural networks. A neural network with active neurons can select the most relevant input arguments, improving prediction accuracy and overcoming the inscrutability of neural networks with logistic or other passive neurons. Figure 2 depicts the GMDH- NN graphically.



**Fig. 2.** Group method of data handling (GMDH)- Neural Network diagram

(Source : Adopted from Kordik et al., (2003))

In the current study the GMDH Shell is used to conduct the regression analysis. The hidden neurons in the network are activated using the linear function.

### Linear Regression

Linear regression is used to predict the relationship between two variables. Mathematically the Linear Regression Equation is as given in equation 1

$$y = c + a_1x_1 + a_2x_2 + \dots + a_nx_n \quad (1)$$

Where,  $x_1, x_2, \dots, x_n$  is the independent variable,  $y$  is the dependent variable. The constant  $c$  is the intercept of the Linear regression and  $a_1, a_2, \dots, a_n$  are multiplicative coefficients of the independent variable.

The descriptive statistical parameters  $R^2$ , Root Mean Square Error (RMSE) and Mean Absolute Percent Error (MAPE) are computed for assessing the best model for the prediction of residential Property Value.

### Coefficient of Determination ( $R^2$ )

Coefficient of Determination ( $R^2$ ) value is a dimensionless value which represents the ability of the model to explain the variation of the predicted value from the observed value. the value of  $R^2$  is between  $[-1, 1]$  where  $-1$  represents the negative correlation and  $1$  represents the positive correlation. Typically, if the value is closer to  $1$  the predictive model 100% explains the observed ground data

$$R^2 = \left[ \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \right]^2 \quad (2)$$

### Root Mean Square Error (RMSE)

RMSE is the standard deviation of the errors. It gauges how widely spaced out the errors are.

In other words, it reveals the degree to which the data are centred around the line of optimal fit.

$$\sqrt{\frac{\sum (P_i - O_i)^2}{n}} \quad (3)$$

Where  $P_i$  is the predicted value for the obtained from the model,  $O_i$  is the observed value obtained from the ground survey and  $n$  is the sample size

### Mean Absolute Percent Error (MAPE)

MAPE is the ratio of the sum of Absolute Percent error (APE) of a predicted value to the total number of observations. Mathematically, MAPE is given by

$$MAPE = \frac{\sum APE}{n} \quad (4)$$

APE is the Absolute Percent error;  $n$  = number of observations Mathematically, APE is given by

$$APE = \frac{|\text{Forecast} - \text{Actual}|}{\text{Actual}} \times 100 \quad (5)$$

In the current study, the predicted value is the output of the model and the Actual Value is the Residential Property value obtained through ground survey.

### Step 5. Validate the model

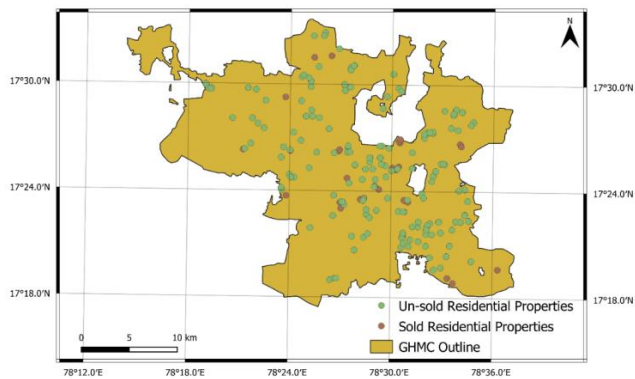
The models thus developed in the step 4 are used for the prediction of property value for the validation datasets consisting of 32 sold out properties details. Also the prediction accuracy are assessed using  $R^2$ , Root Mean Square Error (RMSE) and Mean Absolute Percent Error (MAPE)

## 5. Analysis and Results

The following are the factors that are considered for study in the present research.

1. Total Area
2. Maintenance Cost
3. Number of Bedrooms
4. Furnishing status
5. Availability of Parking
6. Number of Toilets
7. Availability of Power Back
8. Age of the Property
9. Availability of Lift
10. Number of Balconies
11. Facing of the property
12. Availability of Security

Through ground survey and interview with the owners, a total of 234 properties were obtained of which 202 properties to be sold and 32 are sold out properties. The former is used for the identification of significant factors and model development and the later is used to for the validation of the developed model. The figure 4 presents the spatial distribution of the properties obtained.



**Fig. 4.** Spatial Distribution of surveyed Residential Properties

The p-value for all the factors considered are as presented in table 1.

**Table 1.** p-value for the factors influencing residential property value

S.no.	Property facility	p-value
1.	Total Area	$6.7913 \times 10^{-45}$
2.	Maintenance Cost	$5.1522 \times 10^{-7}$
3.	Number of Bedrooms	0.0058612
4.	Furnishing status	0.0086048
5.	Availability of Parking	0.0089551
6.	Number of Toilets	0.009457
7.	Availability of Power Back	0.0152462
8.	Age of the Property	0.0475924
9.	Availability of Lift	0.2140353
10.	Number of Balconies	0.2987305
11.	Facing of the property	0.3958741
12.	Availability of Security	0.4874342

From the table it is clear that the Total Area and Maintenance cost are the most significant factors ( $p$  value  $< 0.001$ ). hence for development of the model the Total Area of the Property and the Maintenance cost of the properties are used as variables.

The combination of the most significant factors are 1. Total area, 2. Total Area and Maintenance Cost, 3. Maintenance Cost. For all the presented combination of input variables the GMDH-NN and Linear regression Models are developed and are presented in table 2 and 3 respectively.

**Table 2.** GMDH-NN and Linear regression model results for training dataset

Combination no.	Method	Dependant (Output) variable	Independent (input) variable	Model Equation	R <sup>2</sup>	RMSE	MAPE
1	GMDH-NN	RPV	TA	$RPV = -1.05587e-12 + N2*1$ Where: $N2 = -9.54693 + "TA"*0.0640043$	0.75	29.92	20.46
	Linear			$RPV = 0.0640*(TA) - 9.5469$	0.75	29.92	20.46
2	GMDH-NN	TA and MC	TA and MC	$RPV = -2.3517e-12 + N4*0.44 + N2*0.56$ Where: $N2 = -2.67166e-12 + N4*1$ ; $N4 = -41.9773 + "TA"*0.0657012 + MC*25.2443$	0.79	27.6	21.47
	Linear			$RPV = 0.0657*(TA) -$	0.79	27.26	21.47

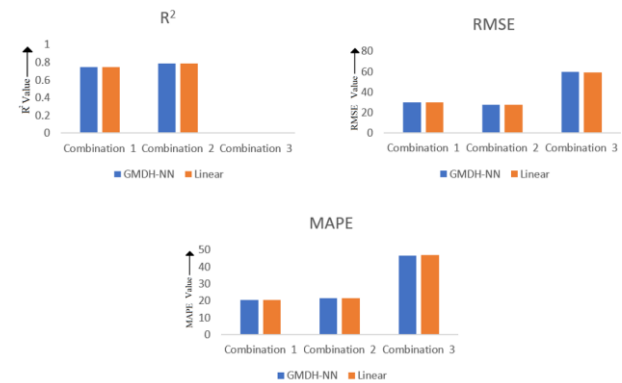
		$25.2443*(MC) - 41.9773$	
3	GMDH-NN	MC	$RPV = 81.6718$
	Linear		$RPV = 11.8*(MC) + 67.7$

Note: RPV-Residential Property Value, TA-Total Area, MC-Maintenance Cost

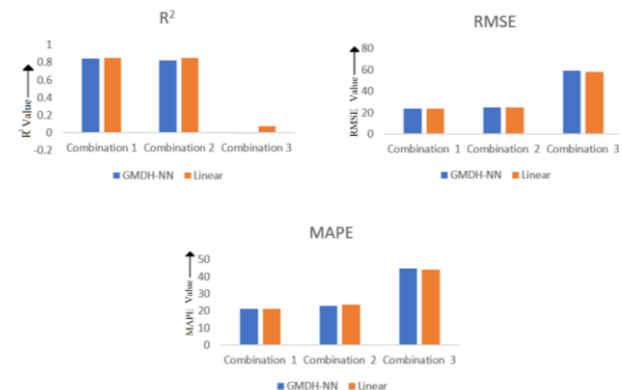
**Table 3.** GMDH-NN and Linear regression model results for validation dataset

Combination no.	Method	R <sup>2</sup>	RMSE	MAPE
1	GMDH-NN	0.842	23.454	21.216
	Linear	0.849	23.454	21.213
2	GMDH-NN	0.826	24.630	22.962
	Linear	0.849	24.630	23.650
3	GMDH-NN	-0.005	59.228	44.688
	Linear	0.077	57.911	44.138

The R<sup>2</sup>, RMSE and MAPE of the models for training and validation datasets are graphically represented as in Figure 5 and Figure 6



**Fig. 5.** R<sup>2</sup>, RMSE and MAPE of training datasets



**Fig. 6.** R<sup>2</sup>, RMSE and MAPE of Validation Datasets

## 6. Discussion

From the table 1 it is evident that the Total Area and Maintenance cost with  $p$ -value  $< 0.001$  are the most significant factors among the identified 12 property facilities influencing the residential property value. the next six factors, in order of their significance are number bedrooms, furnishing status, parking facility, Number of Toilets, availability of Power backup and Age of property with  $p$ -value  $< 0.05$ . Thus, for all the combination of the Total area and Maintenance cost as input variables, the GMDH-NN and Linear Regression Models are developed.



From table 2 and 3 it is clear that for both training and validation datasets, the  $R^2$  is greater than 0.74 and the RMSE and MAPE are less than 30% for the combination 1 considering Total area, and combination 2 considering both total area and maintenance cost as input variables. In addition, there is an improvement in combination 2 results with  $R^2$  changing from 0.748 to 0.785, and the RMSE from 29.92 to 27.60 over combination 1 during training. It is further noticeable that, there is no difference between the statistical measures of GMDH-NN and Linear Regression Models. Since the accuracy of both the models for both the combination is above 70%, any of them can be used for prediction of the Residential Property Value depending on the availability of the data and the software applications. Also, from the same table 2, it is evident that the combination 3 i.e., the consideration of the Maintenance cost as the only variable to predict the Residential Property Value has correlation of almost 0 and the Root Mean Squared Error is as high as 59 %. Hence, inspite of it being a significant facility, the prediction using it alone is not suggestible.

## 6. Conclusion

The computation of Residential Property value is important for all the agents of real estate market. In the current study an attempt has been made to identify the significant facilities contributing to the residential property value in Greater Hyderabad Municipal Corporation (GHMC) region and thus develop the models using them. As compared to the previous works which can more fully be described as qualitative in nature, the current work's approach is extremely quantitative. Also, the claim that there is difference between the output of various methods considered for study is ruled out for the fact that the results obtained in the both Group Methods of Data Handling and linear regression techniques are identical for the most significant factors taken into account as input variables. So, the nearness in model accuracy lies in the identification of the significant factors. Since the model fitting parameters as  $R^2$  is high and error assessment parameters as Root Mean Squared Error (RMSE) and Mean Absolute Percent Error (MAPE) are low, the proposed equation can be directly used to provide a quantitative overview of the residential property values in study area. Further, the methodology adopted in the study can be used for valuation in any region.

This study is based on the assumption that all household have similar tastes and preference and the net impact of all other factors influencing the property value is constant. The reality is not so. Also, it can be observed that, with respect to place and time the property values are liable to vary and the significance of the considered factors may also change. The other factors like quality of construction, the type of material used and natural ventilation of the property may contribute significantly depending on the location and socio-economic spectrum of that particular area. Hence, it is observed and recommended that studies are to be performed over various scenarios to develop a generalized property valuation approach for any area.

## Acknowledgment

The authors acknowledge University Grants Commission, New Delhi, India, for supporting through national fellowship to carry research work. The authors also acknowledge Civil Engineering Department, University College of Engineering, Osmania University Hyderabad, Talangana, India, for providing the facilities to carry out the research work.

## References

- [1] Brandt, S., & Maennig, W. (2011). Road noise exposure and residential property prices: Evidence from Hamburg. *Transportation Research Part D: Transport and Environment*, 16(1), 23–30.
- [2] Burinskienė, M., Rudzkiene, V., & Venckauskaitė, J. (2011). *MODELS OF FACTORS INFLUENCING THE REAL ESTATE PRICE*.
- [3] J, M. S., S. K. Dr.N.C., M. Dr. P., T. N, and J. P. S. “IEEHR: Improved Energy Efficient Honeycomb Based Routing in MANET for Improving Network Performance and Longevity”. *International Journal on Recent and Innovation Trends in Computing and Communication*, vol. 10, no. 7, July 2022, pp. 85–93, doi:10.17762/ijritcc.v10i7.5575.
- [4] Chau, K. W., & Chin, T. L. (2003). A critical review of literature on the hedonic price model. *International Journal for Housing Science and Its Applications*, 27(2), 145–165.
- [5] Chau, K. W., Wong, S. K., & Yiu, C. Y. (2004). The value of the provision of a balcony in apartments in Hong Kong. *Property Management*, 22(3), 250–264.
- [6] Choy, L. H. T., Mak, S. W. K., & Ho, W. K. O. (2007). Modeling Hong Kong real estate prices. *Journal of Housing and the Built Environment*, 22(4), 359–368.
- [7] Ferlan, N., Bastic, M., & Psunder, I. (2017). Influential factors on the market value of residential properties. *Engineering Economics*, 28(2), 135–144. <https://doi.org/10.5755/j01.ee.28.2.13777>
- [8] Fisher, J. D., & Martin, R. S. (1994). *Income property valuation*. Kaplan Publishing.
- [9] Fletcher, M., Gallimore, P., & Mangan, J. (2000). Heteroscedasticity in hedonic house price models. *Journal of Property Research*, 17(2), 93–108.
- [10] Grebler, L., Blank, D. M., & Winnick, L. (1956). *Capital formation in residential real estate*. Princeton University Press Princeton.
- [11] Baes, A. M. M. ., Adoptante, A. J. M. ., Catilo, J. C. A. ., Lucero, P. K. L. ., Peralta, J. F. P., & de Ocampo, A. L. P. (2022). A Novel Screening Tool System for Depressive Disorders using Social Media and Artificial Neural Network. *International Journal of Intelligent Systems and Applications in Engineering*, 10(1), 116–121. <https://doi.org/10.18201/ijisae.2022.274>
- [12] Janmaat, J. A. (2005). *Factors affecting Residential Property Values in a Small Historic Canadian University Town In Nova Scotia. May*.
- [13] Joslin, A. (2005). An investigation into the expression of uncertainty in property valuations. *Journal of Property Investment & Finance*.
- [14] Kordík, P., Náplava, P., Snorek, M., & Genyk-Berezovskyj, M. (2003). Modified GMDH method and models quality evaluation by visualization. *Control Systems and Computers*, 2, 68–75.
- [15] Lenk, M. M., Worzala, E. M., & Shiva, A. (1997). High-tech valuation: should artificial neural networks bypass the human valuer? *Journal of Property Valuation and Investment*.
- [16] McCluskey, W., & Anand, S. (1999). The application of intelligent hybrid techniques for the mass appraisal of residential properties. *Journal of Property Investment & Finance*.
- [17] M. J. Traum, J. Fiorentine. (2021). Rapid Evaluation On-Line Assessment of Student Learning Gains for Just-In-Time Course Modification. *Journal of Online Engineering Education*, 12(1), 06–13. Retrieved from <http://onlineengineeringeducation.com/index.php/joe/article/view/45>
- [18] McCluskey, W. J., Deddis, W. G., Lamont, I. G., & Borst, R. A. (2000). The application of surface generated interpolation models for the prediction of residential property values. *Journal of Property Investment & Finance*.
- [19] McGreal, S., Adair, A., McBurney, D., & Patterson, D. (1998). Neural networks: the prediction of residential values. *Journal of*

- [20] Pandya, A. S., Kondo, T., Shah, T. U., & Gandhi, V. R. (1999). Prediction of stock market characteristics using neural networks. *Applications and Science of Computational Intelligence II*, 3722, 189–197.
- [21] Rodgers, T. (1994). Property-to-property comparison. *The Appraisal Journal*, 62(1), 64.
- [22] Rossini, P. (1997). Artificial neural networks versus multiple regression in the valuation of residential property. *Australian Land Economics Review* Rossini, P. (1997). *Artificial Neural Networks versus Multiple Regression in the Valuation of Residential Property*. *Australian Land Economics Review*, 3(1), 1–12., 3(1), 1–12.
- [23] Selim, H. (2009). Determinants of house prices in Turkey: Hedonic regression versus artificial neural network. *Expert Systems with Applications*, 36(2), 2843–2852.
- [24] Sirmans, G. S., MacDonald, L., Macpherson, D. A., & Zietz, E. N. (2006). The value of housing characteristics: a meta-analysis. *The Journal of Real Estate Finance and Economics*, 33(3), 215–240.
- [25] Ustaoglu, E. (2003). *Hedonic price analysis of office rents: A case study of the office market in Ankara*. Middle East Technical University.
- [26] Yayar, R., & Deniz, G. Ü. L. (2014). Mersin kent merkezinde konut piyasası fiyatlarının hedonik tahmini. *Anadolu Üniversitesi Sosyal Bilimler Dergisi*, 14(3), 87–100.
- [27] Yilmazel, S., Afsar, A., & Yilmazel, Ö. (2017). Analysis of apartments for sale in turkey based on city and region by using big data technologies. *Sakarya İktisat Dergisi*, 6(3), 1–21.