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Cascaded Fuzzy Analytics Based Model for Determining Rental Values of Residential Properties

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Abstract: The world's property marketplace continues to experience enormous growth in infrastructure geared towards enhancing the quality of neighborhoods, such as physical landscaping and aesthetics, which have pushed rental values above reasonable bounds. The practice of ascertaining the market value of properties makes use of underlying key characteristics, especially in cities across the globe. Again, property rental values vary from place to place based on characteristics (or factors). Studies are ongoing in determining the best factors needed to accurately arrive at appropriate market and rental values for properties. This study proposes a cutting-edge approach based on cascaded fuzzy logic controls to pair up distinct property characteristics identified by various professionals and literally works. The housing dataset was collected and used to construct the membership functions, the inference engine, and validate the proposed property rental value model. The outcomes revealed that, the cascaded fuzzy analytics model was the inverse of the regression model, as the minimal MSE (0.05628) supported a good prediction of residential property values when compared to the regression model (*R = 0.7320*) whose value must be close to 1 to be a good estimate. Again, the proposed cascaded fuzzy analytics model (0.05628) was an improvement over the regression model (0.09619) in terms of MSE and standard error of estimation. These revealed the capability of the proposed model in determining residential property prices at a lower error rate than statistical inference approaches like the regression estimation model.

Keywords: Rental Values, Property, Fuzzy Analytics, Accuracy, Fuzzy, Determinants.

1. INTRODUCTION

There is a strong focus among researchers on determining the association between sales prices and transportation infrastructure and property and land values over the past years [1]. Global property prices are on the rise in metropolitan neighborhoods, which has caused housing affordability issues among low-income strata. Young people, new couples, and migrants continue to worry about the affordable accommodation offered by rental homes. Rental markets are strictly operated by private individuals and enterprises. Studies attempt to check housing rental prices to assist governments in providing a healthy real estate market. It became possible to identify the huge variability caused by location, especially in urban areas [2].

The means of improving the decision-making process have continued to attract the attention of scholars and cognitive scientists over the years. The concept of decision-making is considered a cognitive procedure in which the beliefs and preferences of individuals are a major factor. The value of individual preferences is often vague or uncertain to establish with the increasing popularity of Rough Set Theory (RST) [3]. The price estimates of many residential properties cannot be effectively determined without considering a multitude of adjoining factors like returns on investments, location, cosmopolitan nature of the area, rate of crime, nearness to markets, age of the building, housing demands, prevailing economic circumstances, structural features, comfort, and others [4]. Licensing is another form of rental property market around the world where individuals and enterprises purchase or procure properties on the basis of observable quality and safety [5].

In the real estate sub-sector, rate of capitalization is a key consideration for transforming home property value into rent market value or otherwise. The hedonic model is a prominent approach to generating hedonic prices based on property characteristics. Also, the income capitalization method has been utilized to value rental properties and appraise real estate. To this effect, market value is often used to describe economic theory because it is impossible to measure directly. One impartial estimate of market values is the sale price given fair circumstances [6].

The consumption good and investment good of highest value is the housing good because the housing value is the main driver of the property marketplace. The valuation of housing property relies on economic and non-economic causes, which help market players such as professionals

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and consumers. The economic cause is directly related to the prevailing interest rates and income rates of the nation. Whereas the non-economic cause relates to the structural, neighborhood, and location characteristics. The usual practice of ascertaining housing prices, capital values, and rental values is mere speculative and self-regulated by the property owners. The values of rent prices for residential buildings depend on the needs of people, locations, neighborhoods, bathrooms or toilets, and the number of rooms. Again, availability of schools, nearness to markets/shopping malls, electricity supply, water supply, crime prevalence rate, access roads, and nearness to the city center. There are a number of techniques used in the past to achieve this, firstly, hedonic methods involving the use of values of properties to construct price indices for distinct characteristics. It depends on the regression coefficients of the price of the unit of characteristics and degree of relationships in order to determine the rental price values of property. Secondly, artificial intelligence modeling and simulation is a new paradigm for complex systems that depend on flexibility, fuzzy reasoning, and general abstraction. Thirdly, there are widespread inconsistencies in human expertise (the most primitive method) in completing the daunting tasks of rental value determination due to the expansive quantity of variables, uncertainties, and non-linearity [7].
Consequently, several algorithms (such as fuzzy logic, fuzzy cognitive maps, and artificial neural networks) have evolved over time to augment these processes of determining rental values of properties across the globe, which learn structures and underlying patterns in data. [8]. The main contributions of this paper include:

1) To generate the fuzzy rules for determining residential property values from professionals and previous studies
2) To construct a cascaded fuzzy analytics-based model for determining the rental values of properties.
3) To determine the impact of the proposed model on the multi-criteria decision-making process of rental value estimation.

The remaining sections of this paper include: section two is a literature review; section three is research methodology; section four is results and discussion; and the conclusion is in section five.

2. LITERATURE REVIEW

A. *PROPERTY VALUATION*

The world's property market is a tenure encompassing private rented apartments, private owner occupations, and public sector housing. In particular, residential properties come in various types, including tenements, blocks of flats, bungalows, detached and semi-detached duplexes, maisonettes, condominiums, and terraced houses. The land values for residential expansions are a major criterion for deciding the level of economic activity of a nation [9]. Traditionally, the structural settings of cities are a great factor in estimating the quality of land; the farther the land is from city centers, the lower the costs of development and the lower the rental values. More so, location and accessibility, environment, tax rates, and availability of amenities are significant considerations in estimating the rental values of properties [10]. The main issue with real estate or property valuation and investment is uncertainty, which relies on market trends, comparable properties, and the attributes of a property. Though, risk and uncertainty are often used in the sense of knowledge gaps or poor or inadequate information concerning inputs, In particular, risk is used to determine losses arising from decision outcomes. Whereas uncertainty relates to the disparity in a possibility distribution in the case of uncertain occurrences (or residual uncertainty). A probability distribution is a quantitative measure of uncertainty (or objective uncertainty). International Valuation Standards identified three distinct sources of valuation process uncertainty, including market disruption, availability of availability, and method selected for valuation (IVSC, Technical Information Paper 4, Valuation Uncertainty, para 17) [11]. The market disruption is associated with market conditions capable of influencing real estate price movements or price volatility. The input availability occurs in cases of data availability. The comparable issue happens when the appraiser faces a shortage of reliable comparables to deploy (European Valuation Standards, 2016, EVIP 2 Valuation Certainty and Market Risk, para 4.8) [12], [13]

B. *HEDONIC MODELS*

In the case of hedonic models, the factors influencing the prices of housing rentals are uneven at the macro and micro scales. At the macroscale, these factors are increasingly important, including province- or city-wide economic indices. Numerous authors have dissociated the relevance of macroeconomic factors such as the values and prices of housing, including the cost of construction, income gaps, population growth, and other administrative considerations. There are arguments about the same macroeconomic factors and propensities for intra-urban arrangements for the various residential homes. The roles played by available environmental and social amenities bounded by adjoining communities cannot be overemphasized. The determinants of housing rental values and prices across the globe have often been investigated with hedonic models in countries such as Poland, USA, Australia, China, and Switzerland. The assumption held by proponents of the hedonic model is that house value can be determined by its neighborhood, structure, and location characteristics. Consequently, the theorem of the hedonic model enables researchers to connect numerous determinants to the rent price and value of housing properties. In effect, these housing rent price determinants can be linked to educational opportunities, public infrastructure, polycentric urban structure, and proximity to markets and economic activities [2].

C. *FUZZY ANALYTICS*

Fuzzy logic control (or fuzzy logic) is considered one of the top choices of researchers and scholars in their attempts to utilize fuzzy set theory in solving everyday problems. This is most desirable for many complex analyses of systems, which renders traditional quantitative techniques incapable of dealing with them, especially in cases where the source of information is rather imprecise, qualitatively and uncertainly vague. In 1965, Zadeh introduced the idea of fuzzy sets for the purpose of knowledge modeling based on the IF-THEN fuzzy rules called fuzzy logic. Fuzzy logic control is unnecessary for the precise system's model in order to enhance control effectiveness [14], [15] pointed out that fuzzy logic controls' performances are determined by the inputs, lists of rules depicting the logical representation, and the outcomes of the interference systems and applications. In particular, the number of rule lists in the fuzzy logic rule base influences the accuracy of the corresponding outcomes of its inference system. Fuzzy logic controllers have the inherent capability to be easily modified quickly enough to cope with the dynamic changes of diverse systems. Though the performance is highly reliant on human experts, their best is for non-linear and complex control systems [16]. Also, three important configurations are identified for fuzzy logic controls including [16]: 1. Creation of membership functions by alternating a collection of crisp values with fuzzy logic values. 2. Control rules are defined for processing and evaluating rules based on fuzzy logic. 3. The conversion of fuzzy logic values to sets of associated crisp values capable of controlling the signals within the system is known as the de-fuzzification procedure. To this end, numerous methods have been adopted for optimizing fuzzy logic control parameters, including input scaling factors, fuzzy input membership functions, output scaling factors, fuzzy output membership functions, and fuzzy rule base [14]. The researchers applied fuzzy logic control to photovoltaic systems after optimizing them with the particle swarm optimization algorithm, which provided improved speed and performance in numerous atmospheric situations. The fuzzy logic control optimized with the particle swarm optimization algorithm enables stable and reliable MPP search with overshoot. The process of carrying out effective routing of wireless sensor networks through the neuro-fuzzy rule-based cluster formation and routing protocol was developed by [17]. This offered an improved routing algorithm for energy consumption, network lifetime, delays, and packet delivery rates on the Internet of Things. [18] introduced particle swarm optimization in altering the range of membership functions of fuzzy logic control to obtain superior outcomes for indoor localization fuzzy systems and visible light communications. The results enable the system to determine the relative position of a receiver on the basis of the transmitters. Singh et al in [19] introduced an innovative braking system (known as the Eddy Current Braking System), which is contactless and frictionless against a normal braking system using particle swarm optimization with fuzzy logic control. This approach absorbs the energy required to increase the performance of optimal barrier systems by reducing overshoot and settling time. Nguyen et al. in [16] applied genetic algorithm and differential evolution algorithm with fuzzy logic controls for overcoming load-frequency of linked hydroelectric power infrastructure. The control issues of load-frequency control were influenced by steady-state error, overshoots, and settling time based on the approach experimented by the authors. Alfa et al. in [15] implemented genetic algorithm-based optimization of the fuzzy logic control inference system for reducing the redundancy in rule lists at the antecedents and consequents for obtaining better DangoteCem PLC share movements against unoptimized rule lists. Alfa, Yusuf, Misra, & Ahuja in [15] proposed optimization to the antecedents of the fuzzy logic control's rule list to remove redundancy using genetic algorithms. The optimized fuzzy logic controls were evaluated with DangoteCem PLC share price movements, with better outcomes than traditional approaches. Costache et al. in [20] constructed 10 flash flood forecast models based on fuzzy logic with elite machine learning algorithms. The predictive outcomes were superior for all the ensemble techniques for managing natural disasters. Murugesan et al. in [21] adopted the neural fuzzy and fuzzy inference system to enable specialists to detect the stages of chronic renal disease (that is, stage_1, stage_2, stage_3, stage_4, and stage_5) for patients. This approach reduces the risk of mortality, kidney failures, and the associated cost of early diagnosis. Colella et al. in [22] developed a fuzzy inference system for monitoring operating room air quality to assist clinicians in maintaining safe environmental conditions during surgery. It provided the best connection between input data, parameters, and alert levels for air quality conditions. The extreme precision outcomes prevent "Bacteria Infections Post-Surgery" cases in hospital facilities. The capability of fuzzy analytics to support decision-making processes in various fields of endeavor motivated its adoption for the rental property value determination problem undertaken in this paper.

D. RELATED WORKS

Kashkooli et al. in [23] analyzed 120 apartment transactions in Shiraz City, Iran, using the hedonic price model. The nearest subway facility, size of property, location, and age contribute to the price of an apartment. Therefore, it means that the context and characteristics of cities largely determine the prices of residential property, which may require more complex modeling approaches. The supply of school facilities to the economic value of property in Ontario was investigated by Merrall et al. in [24]. The researchers adopted the spatial hedonic approach, which showed that the availability of schools portends higher property values for the neighborhood. Nevertheless, the dynamics could differ in other scenarios and could require more factors for accurate modeling. Poojary and Kumar examined the main motives behind the willingness of customers to transact in residential property purchases in India. The researchers found that the customers were more inclined to consider factors during their decision to buy, such as security, healthiness, value, safety, and location of property. Other factors included neighborhood facilities and accessibility. The study did not apply a specific modeling technique. The concept of macroeconomic factors was highlighted in the study by Zulkarnain and Nawi [25], as impacting enormously on residential property prices like unemployment, wage, GDP, and exchange rate. This is particularly prevalent in developing economies like Malaysia. However, the macroeconomic factors are less reliable for modeling home prices. Government interventions in local city housing development attract higher economic activities, the availability of social amenities, and employment opportunities, which could directly impact residential property pricing and housing market dynamics. The study by Deng [26] indicated that, using hedonic pricing technique treatment on a quasi-natural experiment of neighborhood and structural attributes, the establishment of a key government facility in a place influences the growth of the residential property market in China. However, the study did not consider computer-based approaches. The concept of macroeconomic factors was highlighted in the study by Zulkarnain and Nawi. The study on residential property price movements using demographic factors and conditions of credit was carried out by Shimizu et al. [27]. The researchers discovered that demographic factors, nominal interest rates, monetary regimes, aging population rate, country or region of interest, and availability of residential stocks heavily affect long-run modeling of asset prices. Also, policy decisions on home prices are mostly dependent on credit and demographic attributes. But the mode of study relied on panel data and empirical analysis, which could lead to a less accurate modeling process. Hu et al. in [2] introduced the concept of machine learning algorithms and a hedonic model for determining factors influencing rental property prices, in which proximity to healthcare centers and sub-district job openings were identified as highly influential determinants. Kazimieras et al., in [7], applied the hedonic model for rental shopping valuation during one-to-one marketing. The site's sales rental value, customer satisfaction, economic indicators, attractiveness, social and psychological factors on buyers, indicators of purchasing capacity, and emotional factors all have an influence on hedonic value. The psychological and emotional states of buyers, valence, arousal, and affective attitudes played significant roles in rental shopping valuations. Abdulmalik and Udoekanem in [28] attempted to help real estate investors generate rental income by understanding the characteristics of rental values of commercial complexes in Ilorin, Nigeria. The perceived disparity in rental income was caused by location quality, safety, visibility of the building, and term of the lease. Shitaye in [29] utilized descriptive and inferential statistics to understand the residential rental housing demand and supply in the township of Ethiopia. It was observed that income of households, marital status, number of rooms, access to transportation facilities, and typology of house majorly influenced house rent market value affordability. Also, Lo et al. in [30] examined the relevance of the price-to-rent ratio in assessing the state of the housing markets by real estate owners and policymakers. The researchers considered the cointegration and causal interrelationships among selected macroeconomic factors and price-to-rent ratios in the Mainland China housing sub-sector. The statistical inference showed that foreign investments, large-sized housing units in prime locations, and the foreign exchange rate influenced price-to-rent dynamics. Rahadi et al. in [31] investigated the factors influencing housing prices in two developed markets, namely Malaysia and Indonesia. Using inferential statistics, it was found that the Malaysian property market is uninfluenced by housing physical design, home design and construction, developer and real estate products, development concepts, housing location, property funding, social status, health, law provisions, and external factors. Conversely, residential property prices in Indonesia are impacted by housing location, property funding, and health. Kasraian et al. in [1] identified the regional and local transit and car transport accessibility on the rise in rental home prices in greater Toronto and Hamilton Area. The spatial model showed that the property values are linked to determinants like proximity to transport infrastructure and low-density areas. Several other determinants push the value of rental properties toward structural features. Yanotti and Wright, in [32], undertook a study of residential property prices in Australia in relation to housing supply shortfalls. The data was collected from a rich proprietary loan level of about 1.1 million mortgage requests and house price appreciation. The factors for accessing funds relied on the residential nature of the investment rather than owner-occupation. There was evidence for real estate property investment in non-metropolitan locations, which explains the shortages in metropolitan location choices. Subaşı & Baycanin [33] studied the impact of COVID-19 on the rental housing market and their prices in Turkey. Endeksa datasets from 81 provinces were considered for the study and analyzed with descriptive statistics. The outcomes revealed that high-priced movements were generally recorded through the study area. Also, the pandemic affected rental housing values significantly in positive ways. Kasraian et al., in [1], modeled the applicability of sustainability messages in residential property advertising in English cities. Homebuyers allot value to certain sustainability features and claims from the textual and visual content of listed properties for sale. Therefore, estate agents and developers could leverage sustainability-minded buyers to introduce commentary on a property's sustainability features on materials used for advertising. Yakubovsky and Zhuk in [34] analyzed the roles of macroeconomic fundamentals on the growth of the residential property market in Ukraine. Using historical home property prices and relevant macroeconomic factors, the authors constructed the ARIMAX model for recognizing the effects of multiple predictors. The housing price movements were best predicted by a multidimensional strategy like multiple linear regression. Though there is a need to focus on more ensuing factors in housing markets (such as outside geopolitical influences) with reliable price modeling methods, The Irish property price valuation based on a flexible geo-spatial smoothing technique was undertaken by Hurley and Sweeney [35]. The researchers attempted to overcome the existing method by comparing it to the latest offering for neighboring properties, which is less accurate and less profitable. The spatial hedonic regression model was built to analyze both the spatial and non-spatial contributions of property attributes to rescale value. Despite widespread application of this statistical method, the use of address mislabeling of properties could be less accurate for property turnover prediction. Elnaeem Balila and Shabri in [36] introduced machine learning approaches into Dubai's property price valuation to increase the accuracy of outcomes. The outcomes showed that decision trees, ANN, and linear regression provided higher interpretability, large dataset operability, and less complex datasets, respectively. Nonetheless, the accuracy of these models is affected by data-preprocessing tasks. Lee et al. in [37] utilized a convolutional neural network model, an automated technique, for determining residential property values. The model was validated with sold price data from Greater Sydney, Australia, which improved the accuracy of estimation and information loss. The residential housing price-influencing factors were grouped into structural, location, and neighborhood attributes. Nevertheless, the size of geographical input data, model structures, and visual features of attributes can be improved in subsequent works. A rent estimation model composed of extreme gradient boosting and random forest regression is used for analyzing the relationship between important factors specified in SHapley Additive Explanations feature importance (SHAP FI) and SHAP summary plots used by Lenaers et al. [38]. The findings revealed non-linear associations rather than just linear associations. The summary of related works in terms of authors, scope, area of study, determinants, and weaknesses are listed in Table I. From Table I, there is a slow introduction of machine learning approaches into property rental valuations across the globe. The use of fuzzy analytics is a new form of approach worth investigating when compared to the spatial model, inferential statistics, and hedonic models, which have large inaccuracies.

3. RESEARCH METHODOLOGY

A. DATA COLLECTION AND PREPARATION

This paper collected residential housing rental prices from a public repository (https://www.kaggle.com) for modeling purposes. The dataset file is named housingdataset.csv composed of five column labels (price, area, bedrooms, bathroom, and stories), and 545 rows for the sampled residential property prices in Boston, Massachusetts, USA, of which the first 10 rows are shown in Table II. The data was normalized into the range of [0 1] by dividing with maximum value of each column as shown in Table III.

Thereafter, data was partitioned into ratio 70:30 percent representing the training (first 382 rows) and testing (last 163 rows) datasets similar to the approach in study in [15], [?] [15], [39]. The values of unnormalized and normalized training dataset are presented in Table IV.

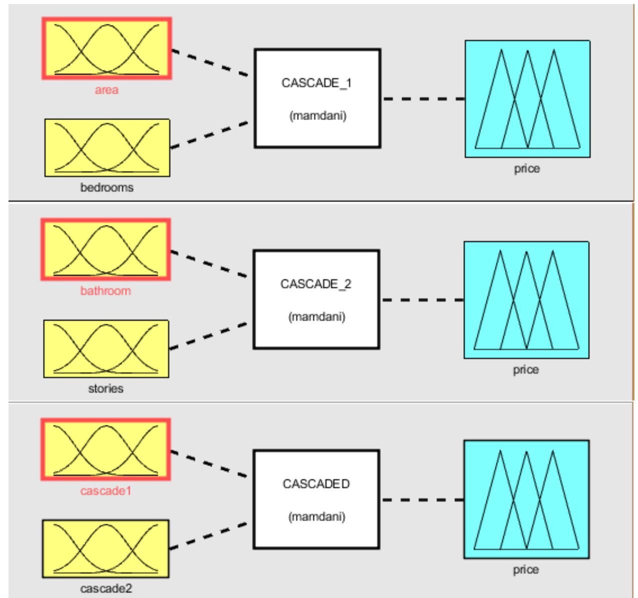

Figure 1. The structure of the cascaded fuzzy analytics model.

B. THE MODEL DESCRIPTION

This paper proposed a Cascaded Fuzzy Analytics based model for determining rental values of residential properties based on the factors defined in Table II. The fuzzy logic engine is capable of taking two input factors and one output factor at time, which implies the two input factors are considered at a time as shown in Figure 1. From Figure 1, the final Cascaded Fuzzy Analytics model is realized in both CASCADE_1 and CASCADE_2 models by passing them as inputs in order to determine the price of residential property by consumers and estate developers. The triangular membership functions are defined for each of the antecedents (that is, area + bedrooms, and bathroom + stories) and the consequent (price) using values defined in Table III as shown in Table V.

From the Table VI, the Cascade Fuzzy Analytics rules-lists are manually generated by human experts using the input and output variables whose indices are shown in Table VI.

C. EXPERIMENTAL SETUP

The minimal hardware and software specification for validating the proposed Cascaded Fuzzy Analytics model for predicting the rental property prices are shown in Table VII.

4. RESULTS AND DISCUSSION

The proposed model in Figure 1 shows the multi-criteria decision-making process of the cascaded fuzzy analytic model. The fuzzy analytics model is best with two antecedents matching a consequent (that is, a 2:1

TABLE I. Summary of reviewed studies

Authors	Scope	Area of Study	Determinants	Methodology
[2]	Rental property prices.	Shenzhen	Healthcare centers, and job openings.	Machine learning algorithms and hedonic model.
[7]	Rental shopping valuation	Lithuania	Site sales rental value, customer satisfaction, economic indicators, attractiveness, social and psychological factors.	Hedonic model.
[32]	Residential property prices.	Australia	Mortgages requests, house price, access to fund, and location choices.	Hedonic model.
[28]	Commercial complexes rental values.	Nigeria	Location quality, safety, visibility of building, and term of lease.	Analysis of Variance.
[29]	Residential rental prices.	Ethiopia	Income of households, marital status, number of rooms, access to transportation facilities, and typology of house.	Descriptive and inferential statistics.
[30]	Housing Rental-to-Prices.	Mainland China.	Foreign investments, large-sized housing units in prime locations, and foreign exchange rate.	Inferential statistics.
[31]	Housing prices.	Malaysia and Indonesia.	Indonesia: housing location, property funding, and healthcare. Malaysia: No significant factors identified.	Inferential statistics.
[33]	Rental housing market prices.	Turkey	Pandemic and external factors.	Inferential statistics.
[1]	Residential properties advertising.	English cities	Sustainability-minded buyers and materials used for advertising.	
[1]	Rental home prices.	Toronto and Hamilton Area.	Proximity to transport infrastructure, and low-high density areas.	Spatial model.
[37]	Residential property values.	Greater Sydney, Australia.	Structural, location and neighborhood attributes.	Convolutional neural network model.
[36]	Residential property prices.	Dubai, UAE	Unspecified.	Decision trees, ANN and linear regression
[35]	Property price valuation.	Ireland	Spatial and non-spatial property attributes.	Flexible geo-spatial smoothing technique.
[34]	Residential property.	Ukraine.	Macroeconomic and outside geopolitical factors.	ARIMAX model.
[26]	Residential property market.	China.	Neighborhood and structural attributes.	Hedonic pricing technique.

TABLE II. The unnormalized sample of the dataset collected.

Price (USD)	Area (m^2)	No. of Bedrooms	No. of Bathrooms	No. of Stories
13300000	7420	4	2	3
12250000	8960	4	4	4
12250000	9960	3	2	2
12215000	7500	4	2	2
11410000	7420	4	1	2
10850000	7500	3	3	1
10150000	8580	4	3	4
10150000	16200	5	3	2
9870000	8100	4	1	2
9800000	5750	3	2	4

TABLE III. The normalized sample of the collected dataset.

Price (USD)	Area (m2)	No. of Bedrooms	No. of Bathrooms	No. of Stories
1.00000	0.45802	0.66667	0.50000	0.75000
0.92105	0.55309	0.66667	1.00000	1.00000
0.92105	0.61481	0.50000	0.50000	0.50000
0.91842	0.46296	0.66667	0.50000	0.50000
0.85789	0.45802	0.66667	0.25000	0.50000
0.81579	0.46296	0.50000	0.75000	0.25000
0.76316	0.52963	0.66667	0.75000	1.00000
0.76316	1.00000	0.83333	0.75000	0.50000
0.74211	0.50000	0.66667	0.25000	0.50000
1.00000	0.45802	0.66667	0.50000	0.75000

TABLE IV. The data preparation procedure.

Column Label	Normalized Value
Price	[0.2711 – 1]
Area	[0.1176 – 1]
Bedrooms	[0.3333 – 1]
Bathroom	[0.2500 – 1]
Stories	[0.2500 – 1]

TABLE V. Membership variables and parameters derivations.

Membership parameters	Lowest	Median	Highest
Consequent (price)	[0.2711 0.4533 0.6355]	[0.4533 0.6355 0.8178]	[0.63556 0.8176 1]
First Cascade			
Antecedent (area)	[0.1176 0.3382 0.5588]	[0.3382 0.5588 0.7794]	[0.5588 0.7794 1]
Antecedent (bedrooms)	[0.3333 0.5000 0.6666]	[0.5000 0.6667 0.8333]	[0.6666 0.8333 1]
Second Cascade			
Antecedent (bathroom)	[0.2500 0.4375 0.6250]	[0.4375 0.6250 0.8125]	[0.6250 0.8125 1]
Antecedent (stories)	[0.2500 0.4375 0.6250]	[0.4375 0.6250 0.8125]	[0.6250 0.8125 1]
Final Cascade			
Cascade_1(price)	[0.5 0.5795 0.6589]	[0.5794 0.6589 0.7383]	[0.6589 0.7383 0.8177]
Cascade_2(price)	[0.5 0.5339 0.5678]	[0.5000 0.5339 0.5678]	[0.5678 0.6016 0.6355]

TABLE VI. The cascaded fuzzy analytics rules-lists.

Rule Number	First Input Parameter	Second Input Parameter	Output Parameter
1	3	3	3
2	3	2	2
3	3	1	3
4	2	3	3
5	2	2	2
6	2	1	2
7	1	3	3
8	1	2	2
9	1	1	1

TABLE VII. The system specifications.

Parameters	Specification
Operating System	Microsoft Windows 10 Home Edition
RAM	6 GB
HDD	1.0 TB
Discrete simulator	MATLAB R2019b
CPU Processor	AMD RYZEN 3 Radeon Graphics
HD Graphics	2.4 GHz
System type	64-bit OS, x64-based processor
Evaluation	Mean Square Error (MSE)

arrangement). The residential property rental value parameters were paired using the closeness of their values after normalization. This concept ensured all parameters were paired and combined in the decision-making process. There are differences between cascaded fuzzy analytics model outcomes and market values for the 163 test datasets utilized for testing, but they are similar in terms of value estimates, as explained in Table VIII. The outcomes of applying cascaded fuzzy analytics to the testing datasets for each of the cascades and the eventual cascaded prediction of rental property prices, as well as the comparable statistical treatment approach (Multiple Regression Model) [29] are given in Table IX.

From Table VI, the values of the MSE computed for the CASCADED model ranged from 0.00016636 to 0.0181, which outperformed the initial CASCADE_1 and CASCADE_2 models utilized for predicting residential property price values. Similarly, the statistical inference treatment on the datasets showed that the CASCADED model better explained the value of residential property at 73.20% when compared to the 60.90% and 58.20% for the original CASCADE_1 and CASCADE_2 models, respectively. The outcomes of both the proposed CASCADED and statistical inference models showed that the values of residential property prices are determined by different factors considered during valuations. The graphical illustrations of the computations for both models are shown in Figure 2. From Figure 2, the cascaded fuzzy analytics model performance is the inverse of the regression model because the minimal MSE (0.05628) is desired to attain a good prediction of residential property values as against the regression model with a high value of R (0.7320) computed. Also, the performance of both models was compared using the MSE and standard error of estimations. The proposed cascaded fuzzy analytics model (0.05628) was superior to the regression model [29] at 0.09619, which implies the superiority of the proposed model in determining residential property prices as shown in Figure 3.

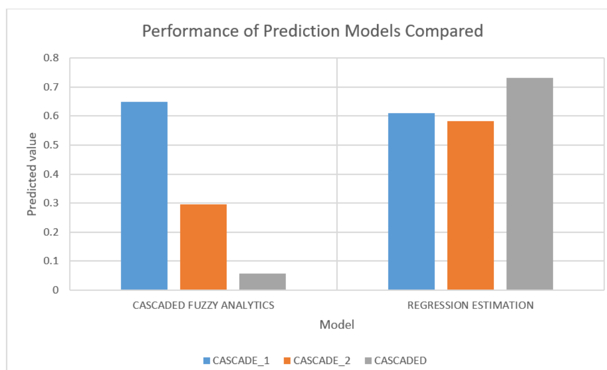

Figure 2. The graphical analysis of model outcomes compared.

5. CONCLUSION

This paper developed a cascaded fuzzy analytics residential rental value prediction based on multiple pairs of determinants and factors. Generally, statistical inferential and hedonic models have dominated research over the years, with large inaccuracies arising from outcomes generated

TABLE VIII. Predicted residential property values.

Area	Bedrooms	Stories	Bathrooms	Price in USD (Market)	Price in USD (Cascade_1)	Price in USD (Cascade_2)	Price in USD (Proposed Model)
3150	3	2	1	3569986	8452158	6650000	6650000
4500	4	2	2	3569986	8452772.4	7571557	7009284.9
4500	2	1	1	3569986	8445500	6650000	6650000
3640	2	1	1	3569986	8445500	6650000	6650000
3850	3	1	1	3535007	8452438.6	6650000	6650000
4240	3	2	1	3500028	8452404	6650000	6650000
3650	3	2	1	3500028	8452470.5	6650000	6650000
4600	4	2	1	3500028	8452787.1	6650000	6650000
2135	3	2	2	3500028	8451541	7571570.3	7011669.6

TABLE IX. The comparison of model outcomes.

Evaluation Metric	Cascaded Model (Proposed)	Multiple Regression Model [29]
CASCADE_1 (MSE)	0.1605 – 0.0499	R = 0.609, R^2 = 0.320
CASCADE_2 (MSE)	0.0775 – 0.0184	R = 0.582, R^2 = 0.339
CASCADED = CASCADE_1 AND CASCADE_2 (MSE)	0.0181 – 0.00016636	R = 0.732,R^2 = 0.536

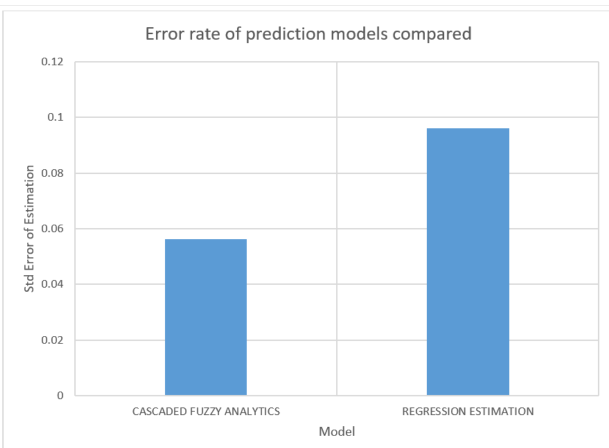

Figure 3. The error rates of estimation models compared.

in numerous similar research areas. Using good prediction measures of the MSE and standard error of estimation, the proposed cascaded fuzzy analytics model (0.05628) was superior to the regression model (0.09619). This means that the proposed prediction model for determining residential property prices was superior to several existing statistical inferential models, like regression estimation. The costs and difficulty of obtaining the real estate transaction data about sold housing properties and its influencing factors motivated the use of secondary data in validating the proposed model. The limitation of the study is the inability to obtain comprehensive data about sold residential property, and influencing factors from real estate practitioners motivated the use of secondary data for the proposed model validation. In future work, the data can be localized to increase the number of determinants of residential housing prices in order to measure the effectiveness of the proposed model. Also, the proposed model can be extended for crude oil price, FOREX, and inflation rate forecasts.

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