Decision Making Advances Volume 3, Issue 1 (2025) 216-227

Decision Making Advances

Journal homepage: www.dma-journal.org
ISSN: 2956-2384

Tourist Arrivals Demand Forecasting Using Rough Set-Based Time Series Models

Haresh Kumar Sharma[1,*], Kriti Kumari[2]

1 Department of Operations Management and Decision Sciences, Birla Institute of Management Technology, Greater Noida, India
2 Department of Mathematics and Statistics, Banasthali Vidyapith, Jaipur, Rajasthan, 304022, India

ARTICLE INFO

Article history:
Received 21 September 2024
Received in revised form 1 December 2024
Accepted 29 December 2024
Available online 5 January 2025

Keywords:

Foreign tourist arrivals; Forecasting; Rough set theory; Time series model.

ABSTRACT

This paper uses different univariate and multivariate autoregression and soft computing models for forecasting qualitative time series data. Rough set theory (RST) is one of the most convenient soft computing methods to investigate the imprecision and ambiguity of an information table by using qualitative dependent and independent variables. Moreover, applications based on rough set theory are used for the classification problem. The rough set is quite different from the other statistical and machine learning data analysis approaches based on mathematical equations. The empirical analysis indicates that the rough set is a highly accurate soft computing model for forecasting FTA data.

1. Introduction

Machine learning approaches are one of the most widely used data science techniques, which describes the relationship between time series variables, commonly termed dependent and independent variables respectively. To estimate the parameters in machine learning methods, supervised and unsupervised approaches based on hyperparameter tuning are used. Machine learning techniques can be applied to classify and regression problems. Therefore, these approaches can be applied to arrival demand forecasting to achieve accurate results. Arrival demand forecasting is very important for the private and public sectors in India. Highly accurate and reliable information regarding the future evolution of tourism is great information for tour operators, hoteliers, and other industries concerned with transportation and tourism policy. Provide a key input into decisions of tourism planning, daily business operation, maintenance planning etc. For any government, planning for the development of tourism invariably starts with an accurate forecasting of FTAs and other factors relating to tourism. This in turn can be achieved only by forming an efficient and effective model for time series forecasting.

* *Corresponding author.*
E-mail address: Hareshshrm@gmail.com

https://doi.org/10.31181/dma31202567

Over the past many years, various statistical time series models such as seasonal autoregressive integrated moving average (SARIMA), vector autoregression (VAR) and vector error correction models have been applied to forecast time series data [1-3]. However, previously used forecasting models are based on statistical assumptions and have huge limitations such as stationary data and independent identical distribution (IID) conditions. Hence, Pawlak [4] introduced the rough set theory (RST) for the classification of objects for imprecise and vague data. Rough set theory pays attention to uncertain or incomplete knowledge in a data set to classify the objects [5-7]. The rough set approach is quite different from the conventional approaches of data analysis that are based on logical statements. The rough set approach discovers the information with the help of data mining techniques. It has its commencement from Artificial Intelligence, one of the branches of the Computer Sciences. The rough set theory has been consistently used as an important tool in various areas (Pamučar *et al.,* [8]; Majumder *et al.,* [9]; Sharma and Kar [10]). For example, Karavidic and Projovic [11] used a Rough set-based multi-criteria decision-making model in security forces operations. Sagar *et al.*, [12] proposed a Multivariate Item Prediction Algorithm (MIPA) based on regression analysis. Faustino *et al.* [13] applied the IF and THEN logical statements for forecasting the electrical charge demand of a region in the USA and Sapucal River in the city of Itajuba. This theory has been also used in the areas of tourism demand analysis for the extraction of decision rules by (Law and Au [14], Goh *et al.,* [15], Hawau'u *et al.*,[16]. Li *et al.,* [6]) analyze and predict the tourism of Tangshan City through the rule-based model. Xiaoya and Zhiben [17] introduce a rough set model for choosing the important factors in the econometric model from many influence factors on domestic tourism income in Hong Kong. Goh and Law [18] used the rough set theory to generate the decision rules for tourism forecasts in Hong Kong from 1985 to 2000. They found that the accuracy of the rough set model was 87%. However, no applications have tried to compare the forecasting performance of rough set and time series models for seasonally adjusted FTAs data. The paper takes one step ahead to simplify this gap. Hence, this paper has considered those issues which have been previously ignored.

In the paper, an attempt has been made to forecast seasonally regulated FTAs in India by using various time series models and rough sets. Monthly data for identifying the undefined connection between variables like tourist arrivals from the USA, foreign exchange earnings and exchange rate was obtained from the Ministry of Tourism, Government of India site [19]. The period selected for obtaining the data was between January 2003 to December 2012. Furthermore, various univariate and multivariate time series models could be added [20-22]. The forecasting performance of several models has been compared using PCCA criteria.

The paper's presentation is as follows: Section 2 presents a rough set model and its theoretical concepts. Section 3 describes the forecasting accuracy criterion. Section 4 describes the empirical results related to rough set and time series models. Section 5 describes the forecasting performance of different models. The last section, section 6, presents the summary and conclusions.

2. Rough set theory (RST)

A new mathematical approach has been drawn for the rough set theory for altering problems like inaccuracy and vagueness. The method developed arranges the information in time series data with their samples, conditional attributes (C) and decision attributes (D) [23].

Condition and decision attributes are similar to the dependent and independent variables, respectively. The main concept of the model is based on indiscernible (IND) or similar relations between the objects. The indiscernibility relation gives an idea about the similar objects in an information system. Further, the information system of the rough set is given by

$$I = (U;\ P;\ V),$$

where U = universe with a finite set of N objects $(x_1;\ x_2;\ x_3; ::: ;\ x_N)$, P = finite set of n attributes $(p_1;\ p_2;\ p_3; ::: ;\ p_n)$, and V = domain values of attributes P.

Let x and y be two objects, where x, y ∈ U in I with a set of attributes A, where $A \subseteq P$. Then x and y are called indiscernible by a set of attributes A, denoted by $IND\ (A)$. Table 1 shows a hypothetical example of an information table based on tourism demand. An information system can be created via dependent and one or more independent variables. Dependent and independent variables are treated as conditions (C) and decision attributes (D).

The rough set theory can be expressed in the sense of two approximation sets called lower approximation (LA) and upper approximation (UA) of a set X. For a given information system with a set of condition attributes A, and a given set X, the LA and UA, indicated by $\underline{A}(X)$ and $\overline{A}(X)$
are given by

$$\underline{A}(X) = \{x|[x]_A \subseteq \mathrm{X}\} \tag{1}$$

$$\overline{A}(X) = \{x|[x]_A \cap \mathrm{X} \neq \emptyset\} \tag{2}$$

The set $\underline{A}(X)$ is known as the set of all components of U which can be surely classified as a member of X in the knowledge A, whereas $\overline{A}(X)$ is the set of elements of U that can be probably classified as member of X involving knowledge A.
The boundary region, say, $B_{NA}(X)$ is a set of members which cannot decisively be classified into
X consisting knowledge A. The boundary region of an exact set is the empty set if LA and UA sets are similar. In the adverse case, if the boundary region is nonempty then the set X is referred to as a rough set with respect to A:

$$B_{NA}(X) = \overline{\mathrm{A}}(\mathrm{X}) - \underline{\mathrm{A}}(\mathrm{X}) \tag{3}$$

In rough set analysis attribute reduction is one of the key elements which can reduce attributes from a data set and generate the minimal adequate subset of attributes for an information system. Reduct and core are two important concepts of rough set theory. A minimal adequate subset of attributes is known as a reduct. The reduct is the essential part of an information system and the core is the set of all important attributes. The core is the common element of all reducts.

The most important stage of rough set theory is the creation of decision rules for a given information system for the prediction of new objects. The advantage of this approach is that it can be useful in predicting the future of time series by employing IF and THEN logical statements from an information system. The `IF and THEN' logical statement is called the rule-based model. It is the simplest approach that has simplified the relationship between the dependent and independent variables in terms of decision rules.

Table 1
Hypothetical example of decision table

		Condition attributes			Decision attribute
Time	Objects	C1	C2	C3	D
t1	January	H	L	L	M
t2	February	H	L	L	M
t3	March	H	L	L	M
t4	April	H	L	L	H
t5	May	H	L	L	L
t6	June	M	M	M	L
t7	July	M	M	M	L
t8	August	M	M	M	L
t9	September	M	M	H	H
t10	October	L	H	H	H
t11	November	H	H	H	H
t12	December	H	H	H	M

3. Proposed approach based on rough set

This study applied a rough set approach to forecast seasonally adjusted FTAs in India, incorporating IF and THEN decision rules. There are four main steps in the rough set analysis, i.e., information system, dependency of attributes, decision rules and accuracy. The overall process of the proposed approach is presented in Figure 1 As the several steps.

Step 1. Data collection and problem classification

Understanding a problem and setting objectives is the most critical step required when extracting useful knowledge. Tourism factors should be carefully studied to define the dependency of arrivals with different factors.

Step 2. RST modeling

After creating an information system, evaluate the dependency between the condition and decision attributes via quality of classification.

Step 3. Indispensable attribute

To identify the important attribute of the analyzed information table, the reduct and core are used by employing dependency of attribute and accuracy of approximation.

Step 4. Generation of decision rules

The decision rules are derived from an in-sample information table, and accuracy is used to check the performance of the rough set model.

4. Empirical results

In this study monthly seasonally adjusted (FTAs), foreign exchange earnings (FEEs), exchange rate (EXR) and tourist arrivals from the USA in India (USAFTAs) from $2003{:}\,1 - 2015{:}\,12$ are used. The time series data are obtained from http: www.indiastat.com. Here, FTAs are used as a decision attribute and FEEs, EXR and USAFTAs are three condition attributes. Also, rough set modelling and forecasting have been explored with Rough Set Data Explorer (ROSE2) software (Predki *et al.* [24]).

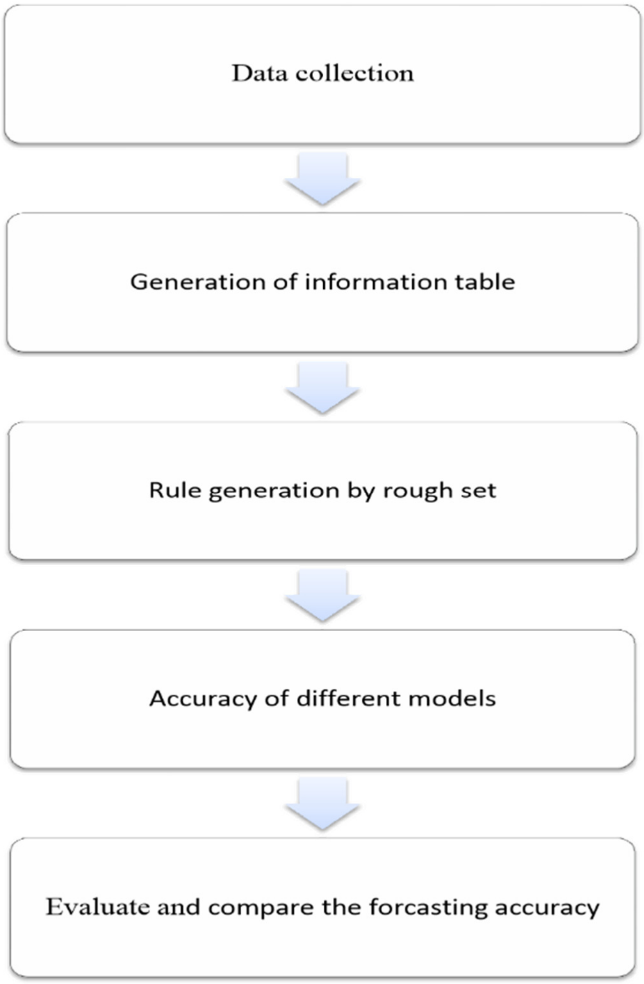

Fig. 1. The framework of the rough set analysis for FTAs data

4.1 Rough set analysis

In this section, all the dependent and independent variables, FTAs, EXR, FEEs and USAFTAs are arranged in an information table for the rough set analysis, reported in Table 2. Thereafter min-max normalization method is used to normalize the dependent and independent variables in the range ($0\ to\ 1$). The normalized values (NV) are categorized into three classes: low (IF $0\ <\ NV\ \leq\ 0.3$), average (IF $0.3\ <\ NV\ \leq\ 0.7$), high (IF $NV >\ 0.8$).

Normalization is done to transform quantitative data into qualitative data. The normalization (Nt) method is defined as:

$$Norm_t = \frac{Akt - Amin}{Amax - Amin} \tag{4}$$

where, Akt is the set of actual and single forecasts time series variables, $Amax\ and\ Amin$ are the Minimum and maximum values of Akt, k =1,2, . . .

The normalized decision table for tourism demand is reported in Table 3 with three condition attributes and one decision attribute. Hence, the decision table is used for the rough set modelling and forecasting.

In the next step, the accuracy and quality of classification have been evaluated that explain the efficiency of three decision classes low, average and high in a decision table. According to Table 4, the accuracy of decision class high in demand is more consistent than low and average. Also, the overall dependency of condition and decision attributes is 0.975. Hence, the three attributes, EXR, FEEs and USAFTAs are indispensable for FTAs by 97% during the rough set analysis.

Further, 120 objects are analyzed and 8 decision rules were generated by using rough set theory. The results of decision rules are given in Table 5. These 8 rules are applied to forecast tourist arrivals to India. From Table 5, the rules 2 has the highest support among all the decision rules. It shows that rule 1 is the strongest rule for the forecasting of tourist arrivals. Also, the robustness of decision rules has been calculated using a forecasting criterion, PCCA. The obtained results are exhibited in Table 6. The average accuracy of decision rules is 96.67%. In the next section performance of the rough set model has been compared with other time series models.

Table 2
Information table for seasonally adjusted FTAs

Month	Year	FTAs	EXR	FEEs	USFTAs
Jan	2003	220663.4	48.29079	1218.347	34125.57
Feb	2003	214113.3	47.87657	1162.308	32385.98
Mar	2003	197922.1	47.97966	1091.559	27872.45
Apr	2003	194947.8	48.04057	1292.333	25922.51
May	2003	199274.8	46.91052	1368.664	29842.68
Jun	2003	227177.3	46.38089	1543.875	32520.38
Jul	2003	241627.7	46.43854	1508.736	34029.24
Aug	2003	242146.7	45.56906	1590.431	34025.93
Sep	2003	250095.7	45.49996	1623.421	39022.93
Oct	2003	255075	45.08263	1463.81	38351.83
Nov	2003	240152.6	45.15619	1404.163	39191.71
Dec	2003	238411.2	45.41764	1383.803	38177.73
…	…	…	…	…	…
Jan	2012	548008.6	50.17494	6980.603	81516.9
Feb	2012	555222.4	49.15709	6852.94	70644.47
Mar	2012	549409.2	51.67118	7140.196	72518.44
Apr	2012	542154.7	53.28034	7560.093	80167.65
May	2012	527345.5	56.28515	7507.405	83704.39
Jun	2012	558383.2	56.18289	7927.182	103099.9
Jul	2012	520878.5	56.16808	8500.192	100817.00
Aug	2012	526536.2	55.38007	8527.719	92721.3
Sep	2012	537945.2	52.29469	8543.512	86736.16
Oct	2012	544754.6	53.83999	8399.652	81564.22
Nov	2012	579495.1	53.60202	8613.674	87557.26
Dec	2012	562271.4	54.55226	8384.687	90892.38

Table 3
Decision table for RST

EXR (C1)	FEEs (C2)	USAFTAs (C3)	FTAs (D)
1	0	0	low
1	0	0	low
1	0	0	low
1	0	0	low
1	0	0	low
1	0	0	low
1	0	0	low
1	0	0	low
1	0	0	low
1	0	0	low
1	0	0	low
1	0	0	low
…	…	…	…
1	0	0	Low
1	2	3	High
1	2	2	High
2	2	2	High
2	2	3	High
2	2	3	High
2	2	3	High
2	2	3	High
2	2	3	High
2	2	3	High
2	2	3	High
2	2	3	High
2	2	3	High

Table 4
Accuracy and quality of classification

Demand	Number of objects	LA	UA	AC	QC
Low in demand	24	22	25	0.88	
Average in demand	62	61	64	0.9531	0.975
High in demand	34	34	34	1	

Table 5
Decision rules for FTAs

No.	Decision rules	Support
1	IF (USAFTAS = 0) THEN (FTAs low)	22
2	IF (FEES = 1) AND (USAFTAs = 1) THEN (FTAs average)	48
3	IF (FEES = 1) AND (USAFTAs = 2) THEN (FTAs average)	9
4	IF (FEES = 2) AND (USAFTAs = 1) THEN (FTAs average)	3
5	IF (EXR= 0) AND (FEES = 0) THEN (FTAs average)	1
6	IF (USAFTAs = 3) THEN (FTAs high)	29
7	IF (FEES = 2) AND (USAFTAs = 2 THEN (FTAs high)	5
8	IF (EXR = 1) (FEEs = 0) AND (USAFTAs= 1) THEN (FTAs low OR average)	3

Table 6
Forecast accuracy of decision rules

Actual FTAs	Forecasted FTAs	Objects
Low	Low	24
Low	Average	0
Low	High	0
Average	Low	2
Average	Average	60
Average	High	0
High	Low	0
High	Average	2
High	High	32
Average accuracy in (%)		96.67

4.2 Time series models

Time series models like Naive I and Naive II, VEC and Grey Model have been applied quite persistently for predicting non-stationary time series data. The approach here is to identify a more accurate model for predicting FTAs in India. The approach is utilized by various time series data sets that have been mentioned in the following subsections.

Time series models like Naive I and Naive II, VEC and Grey Model have been applied quite persistently for predicting non-stationary time series data. The approach here is to identify a more accurate model for predicting FTAs in India.

4.2.1 Naive models

Naive I use the time series data of the preceding time series data, for instance in order to calculate the details for June 2003 the data that will be taken into consideration will be from May 2003, similarly, data prediction for November 2012 will be done on the basis of November 2012. Thus Naive I method can be efficiently used for estimating the foreign tourist arrivals in India. However, the Naive II method utilizes a slightly different approach, if the value is to be calculated for January 2013, the data taken into consideration will be of December 2012 multiplied by the growth rate of January 2013 in comparison with the previous month. The obtained data from the methods Naïve I and Naïve II is provided in Table 7.

Table 7
Forecasting results of Naive models

Month/Year	Actual	Naive I	Naive II
Jan-13	579649	562271.4	545559.6
Feb-13	561234.4	579649	597563.7
Mar-13	579372.1	561234.4	543404.8
Apr-13	545787.3	579372.1	598096
May-13	587866.7	545787.3	514149.3
Jun-13	581359.4	587866.7	633190.4
Jul-13	542986	581359.4	574924.1
Aug-13	574632.3	542986	507145.5

Month/Year	Actual	Naive I	Naive II
Sep-13	592841.4	574632.3	608123
Oct-13	585484.3	592841.4	611627.5
Nov-13	606551.5	585484.3	578218.5
Dec-13	613504.2	606551.5	628376.8
...	...	...	...
Jan-16	679174.6	681563.2	688863.5
Feb-16	690367.4	679174.6	676794.4
Mar-16	740148.2	690367.4	701744.7
Apr-16	725568.4	740148.2	793518.6
May-16	744949.7	725568.4	711275.8
Jun-16	708624.4	744949.7	764848.7
Jul-16	789131.9	708624.4	674070.4
Aug-16	791638	789131.9	878785.9
Sep-16	803855.4	791638	794152.1
Oct-16	738102.1	803855.4	816261.4
Nov-16	736368	738102.1	677727.3
Dec-16	774365.3	736368	734638

4.2.2 Estimated results of the Grey model

Using accumulated generation operation (AGO), the original FTAs time series data is transformed into a Grey differential equation to start the Grey model. Inverse accumulated generation operation (IAGO) has been used to carry out the entire Grey model process. Additionally, the parameters for the Grey differential equation are estimated using the least squares method. For the Grey model, the estimated values of parameters a and b are 266972.1 and -0.006628205, respectively. Additionally, the Grey model's correctness is assessed using the posterior variance ratio (C). According to Julong [20], a score of C< 0:35 suggests that the Grey model is highly accurate. The great accuracy of the Grey model for the FTAs data is indicated by the computed value of C, which is 0.2202.

4.2.3 Vector error correction model

In order to estimate more than one relation between a set of time series variables Vector error correction (VEC) has been predominantly applied. Now, the VEC model will be fitted for FTAs time series data. In the VEC model, the first difference is used to achieve a stationary series. The order of the VEC model has been selected using a minimum AIC value. The results obtained using AIC for six lags are reported in Table 8. The parameters that are analyzed with the VEC model can be measured using the ordinary least square (OLS) method.

Furthermore, to check the importance of autocorrelation in the error terms, the Durbin-Watson Test is applied. This also evaluates the robustness of the VEC model. When analyzed the Durbin Watson tables reveal that there is no autocorrelation between the values of the test statistic of the residuals as compared to the critical values of the table. In [25] autoregressive conditional heteroscedasticity (ARCH) LM is a test that is applied for testing the issue of heteroscedasticity in residual. The result obtained after calculating the chi-square value (6.3877) and p-value (0.0942) of the ARCH LM test states the absence of heteroscedasticity.

Table 8
AIC value for the VEC model

Number of lags	AIC
1	5698.144
2	5665.936
3	5618.562
4	5576.01
5	5535.977
6	5504.039

5. Forecasting performance of different models

The forecasting performance of different models has been evaluated based on the forecasting results obtained from different models. The results of accuracy are reported in Table 9. The accuracy has been calculated by evaluating corrected actual and forecasted values. In Table 9, the Grey model performs the least accuracy in forecasting because it has a lesser corrected classified forecasted value. It also revealed that the RST model has the highest corrected classified value as compared to other time series models. Therefore, RST is a highly accurate model for forecasting seasonally adjusted FTAs data.

Table 9
Results of Forecasting Accuracy

Models	RST	Naive I	Naive II	Grey	VEC
Accuracy	96.29	85.18	75.92	64.81	85.18
TPE	2	16	26	38	16

6. Conclusions

The rough set model has become a popular machine-learning approach in time series forecasting. The advantage of the approach is that it uses IF and THEN logical statements from an information table (decision table) for forecasting time series data. Another advantage of this method is that it is free from any statistical assumptions. The rough set approach discovers the information with the help of data mining techniques by applying decision rules. In rough set forecasting, it is important to organize the information table in terms of rows and columns using dependent and independent variables. The row indicates an object, and the column represents the time series attributes. The rough set approach discovers the information with the help of data mining techniques by applying decision rules.

The article's contribution is in the integration of multivariate autoregression with soft computing models for the prediction of qualitative time series data. Our empirical analysis indicates that the performance of the rough set-based forecasting model is significantly more accurate than that of other classical time series methods. In rough set forecasting, it is important to organize the information table in terms of rows and columns using dependent and independent variables. The row indicates an object, and the column represents the time series attributes.

In future research, RST and machine learning-based hybrid models would be beneficial to forecast time series data such as share market data, train passenger prediction, and supply and demand forecasting data.

Acknowledgements
The infrastructural support provided by BIMTECH, Greater Noida in completing this study is gratefully acknowledged.

Conflicts of Interest
The authors declare no conflict of interest.

References
[1] Dritsaki, N. (2004). Cointegration analysis of German and British tourism demand for Greece, Tourism Management, 25(1), 111-119. https://10.1016/S0261-5177(03)00061-X
[2] Kulendran, N. (1996). Modelling quarterly tourist flows to Australia using Cointegration analysis. Tourism Economics, 2(3), 203-222. https://doi.org/10.1177/135481669600200301
[3] Kulendran, N. and King, M. L. (1997). Forecasting international quarterly tourist flows using error-correction and time series models, International Journal of Forecasting, 13(3), 319-327. https://doi.org/10.1016/S0169-2070(97)00020-4
[4] Pawlak, Z. (1982). Rough sets, International Journal of Computer and Information Science, 11, 341-356. https://doi.org/10.1007/BF01001956
[5] Celotto, E., Ellero, A. and Ferretti, P. (2012). Short-medium term tourist services demand forecasting with Rough Set Theory, Procedia Economics and Finance, 3, 62-67. https://10.1016/S2212-5671(12)00121-9
[6] Li, J., Li F., and Zhou, G. (2011). Travel Demand Prediction in Tangshan City of China Based on Rough Set, Springer-Verlag Berlin Heidelberg, 440-446. https://doi.org/10.1007/978-3-642-25255-6_56
[7] Singh, A., Singh, A., Sharma, H. K., & Majumder, S. (2023). Criteria selection of housing loan based on dominance-based rough set theory: An Indian case. Journal of Risk and Financial Management, 16(7), 309. https://doi.org/10.3390/jrfm16070309
[8] Pamučar, D., Stević, Ž., & Zavadskas, E. K. (2018). Integration of interval rough AHP and interval rough MABAC methods for evaluating university web pages. Applied soft computing, 67, 141-163. https://doi.org/10.1016/j.asoc.2018.02.057
[9] Majumder, S., Singh, A., Singh, A., Karpenko, M., Sharma, H. K., & Mukhopadhyay, S. (2024). On the analytical study of the service quality of Indian Railways under soft-computing paradigm. Transport, 39(1), 54-63. https://doi.org/10.3846/transport.2024.21385
[10] Sharma, H. K., & Kar, S. (2018). Decision making for hotel selection using rough set theory: A case study of Indian hotels. International Journal of Applied Engineering Research, 13(6), 3988-3998.
[11] Karavidic, Z., & Projovic, D. (2018). A multi-criteria decision-making (MCDM) model in the security forces operations based on rough sets. Decision Making: Applications in Management and Engineering, 1(1), 97-120. https://doi.org/10.31181/dmame180197k
[12] Sagar, P., Gupta, P., & Tanwar, R. (2021). A novel prediction algorithm for multivariate data sets. Decision Making: Applications in Management and Engineering, 4(2), 225-240. https://doi.org/10.31181/dmame210402215s
[13] Faustino, P.C., Pinheiro, A.C., Carpinteiro, A.O. and Lima, I. (2011). Time series forecasting through rule based models obtained via rough sets, Artificial Intelligence Review, 36, 299-310. https://doi.org/10.1007/s10462-011-9215-0
[14] Law, R. and Au, N. (2000). Relationship modelling in tourism shopping: a decision rules induction approach, Tourism Management, 21, 241-249. https://doi.org/10.1016/S0261-5177(99)00056-4
[15] Goh, C., Law, R. and Mok, H. M. K. (2008). Analyzing and forecasting tourism demand: A rough sets approach, Journal of Travel Research, 46, 327-338. https://doi.org/10.1177/0047287506304
[16] Hawau'u W-Y, Samuel OA, Gabriel OB, Bamidele FO (2022). Assessment of passengers' satisfaction on service quality of Arik airline at Nnamdi Azikwe international airport, Abuja, Nigeria. Indian Journal of Engineering, 19(51), 43-54.
[17] Xiaoya, H., & Zhiben, J. (2011). Research on econometric model for domestic tourism income based on rough set. In Innovative Computing and Information: International Conference, ICCIC 2011, Wuhan, China, September 17-18, 2011. Proceedings, Part II (pp. 259-266). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-23998-4_37

[18] Goh, C. and Law, R. (2003). Incorporating the rough sets theory into travel demand analysis, Tourism Management, 24, 511-517. https://doi.org/10.1016/S0261-5177(03)00009-8
[19] Socio-economic statistical information, http://www.indiastat.com. Accessed 12 December 2023.
[20] Julong, D. (2002). Grey prediction and grey decision. Huazhong University of Science and Technology Press, Wuhan, 71-75.
[21] Kumari, K., Sharma, H. K., Chandra, S., & Kar, S. (2022). Forecasting foreign tourist arrivals in India using a single time series approach based on rough set theory. International Journal of Computing Science and Mathematics, 16(4), 340-354. https://doi.org/10.1504/IJCSM.2022.128652
[22] Agboola Olasunkanmi J, Roland Uhunmwangho, A. Big-Alabo, Esoasa Omorogiuwa (2021). Artificial Neural Network for Long-term Industrial Load Forecast: Trans-Amadi Industrial Layout, Nigeria. Indian Journal of Engineering, 18(49), 212-221
[23] Pawlak, Z. (1991). Rough sets, A Theoretical Aspect of Reasoning about data, Kluwer Academic Publisher, Boston. https://doi.org/10.1007/978-94-011-3534-4
[24] Predki, B., Słowiński, R., Stefanowski, J., Susmaga, R., & Wilk, S. (1998). ROSE-software implementation of the rough set theory. In Rough Sets and Current Trends in Computing: First International Conference, RSCTC’98 Warsaw, Poland, June 22–26, 1998 Proceedings 1 (pp. 605-608). Springer Berlin Heidelberg. https://doi.org/10.1007/3-540-69115-4_85
[25] Engle, R.F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the variance of United Kingdom Ination. Econometrica 50(4): 987-1008. https://doi.org/10.2307/1912773