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Fuzzy Time Series Modeling for Forecasting Iraq's Gasoline Imports
An International Business Perspective

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Abstract:
In the modern business context, the ability to predict future events based on data and analysis is crucial. Forecasting enables local and international companies to plan deliberately, enhance operations, and make informed decisions, thus contributive to long-term accomplishment. One of the essential elements for making accurate forecasts is the use of historical data. this paper addresses the challenges and difficulties of making decisions regarding investments, In view of the challenges associated with importing gasoline in Iraq, stemming from the market's complexity, and the need to formulate plans and strategies for future initiatives, This paper compared two forecasting methods, the first using fuzzy time series theory (an artificial intelligence concept that can be used for forecasting techniques), including the Chen-Hsu method ,The second is represented by the use of the Autoregressive Moving Average model(ARIMA), which is also used in forecasting, in addition to discussing the concept of fuzzy logic to develop the basis of fuzzy time series. Applying these methods can lead to results with a lower error rate to determine the more suitable method from an international business perspective, a practical issue is analyzed using both approaches.

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التنبؤ بواردات العراق من البنزين باستخدام نماذج السلاسل الزمنية الضبابية من منظور الشركات الدولية

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المستخلص

في سياق الأعمال الحديثة تُعد القدرة على التنبؤ بالأحداث المستقبلية استنادًا إلى البيانات والتحليلات أمرًا بالغ الأهمية حيث تستطيع الشركات المحلية والدولية من وضع الخطط المدروسة وتحسين العمليات واتخاذ قرارات صائبة، مما يُسهم في تحقيق إنجازات طويلة الأجل. يُعد استخدام البيانات التاريخية أحد العناصر الأساسية لوضع تنبؤات دقيقة. يتناول هذا البحث تحديات وصعوبات اتخاذ القرارات المتعلقة بالاستثمارات، منها صعوبة قراءة سوق استيراد البنزين في العراق نظرًا لتعقيده، ورغبة الشركات في وضع خطط واستراتيجيات لتحقيق الاهداف المستقبلية. وقد طبق هذا البحث مقارنة بين طريقتان للتنبؤ الاولى باستخدام نظرية السلاسل الزمنية الضبابية(وهو مفهوم من مفاهيم الذكاء الاصطناعي يُمكن استخدامه لإجراء تقنيات التنبؤ) بما في ذلك طريقة (تشن وهسو) والثانية متمثلة باستخدام نموذج الانحدار الذاتي المدمج مع المتوسط المتحرك((ARIMA الذي بدوره ايضا يستخدم في التنبؤ بالاضافة الى مناقشة مفهوم المنطق الضبابي لتطوير أساس السلاسل الزمنية الضبابية. باستخدام تلك الطرق يُمكن تحقيق نتائج بمعدل خطأ أقل وذلك لتحديد الطريقة الأنسب من منظور الشركات والأعمال الدولية حيث يعمل على تحليل الموضوع عمليا باستخدام كلا النهجين.

الكلمات المفتاحية: الأعمال او الشركات الدولية، التنبؤ داخل السلسلة،التنبوء خارج السلسلة، السلاسل الزمنية الضبابية، طريقة تشين، نموذج الانحدار الذاتي المدمج مع المتوسط المتحرك ARIMA، متوسط الخطأ المطلق AME.

1. Introduction

The growing availability of historical data, along with the rising need for production forecasting, has highlighted the significance of Time Series Forecasting (TSF). TSF allows for the projection of future outcomes over long periods and, despite the limitations of traditional methods, supports predicting system behavior by leveraging both past and present information

Forecasting is an activity estimating future trends and events for an extended period of time, a critical challenge that spans multiple fields, including industry and business, economics, government, medicine, society, environmental science, politics, and finance [Montgomery C Douglas,2015, 105].

In time series, data are expressed as points organized in chronological order, creating a sequence of equally spaced discrete-time observations. Forecasting is the process of estimating future values by examining these observed data points [Büyükşahin, Ü.Ç, 2019, 155-156].

determining the actions for appropriate timing to importing gasoline and aims to explore future investment opportunities and emphasize the significance of advancing and refining time series forecasting models, as well as evaluating their effectiveness. In light of Iraq's unstable conditions, the study seeks to identify an accurate model for forecasting gasoline imports by comparing the accuracy of the Chen and Hsu method with the Auto ARIMA (p, D, q) model. Both methods are applied to 11 years of historical gasoline import data in Iraq, allowing a comparison between forecasting (using the Chen method) [Chen, S.M.,1996, 314] and prediction (using the Auto ARIMA model).

In international business and economics, forecasting plays a crucial role in guiding managerial decisions, and it is essential to minimize forecasting errors as much as possible.

The Chen model was chosen because it has an exceptionally high level of accuracy.

2. Theoretical Part

2.1. Fuzzy time series

let S is be universal set, where S = {S1, S2, ..., Sn}, then the fuzzy set B of S is defined as follow:

$$B = \frac{f_B(S_1)}{S_1} + \frac{f_B(S_2)}{S_2} + \frac{f_B(S_3)}{S_3} + \cdots + \frac{f_B(S_n)}{S_n} \quad ....(1)$$

here f_B is a membership function of the fuzzy set B, defined as f_B: S→ [0,1], the value $f_B(si)$ denotes the degree of membership of S; in the fuzzy set B, where 1 ≤ i ≤ n [Nurkhasanah,2015, 917].

Definition 2.1.1. [Song, Q.,1994,62]

Let (t = ...,0,1,2,...), a subset of R, serve as the universe on a set of fuzzy $f_i(t)$ (i = 1,2, ...). Then, F(t) is called a fuzzy time series on (t).

From up definition, F(t) can be regarded as a linguistic variable and f_i(t) (i = 1,2,...) it represents a linguistic value of F(t), where f_i(t) is itself a fuzzy set . therefore, F(t) functions as a mapping at time t.

Definition 2.1.2. [Chen, S.M.,1996, 318–319**]**

If F(t) is brought on by F(t-1), i.e., F(t-1)→F(t) and R(t, t -1) is the fuzzy relationship between F(t-1) and F(t) ,it can be stated as follows:

$F(t) = F(t-1) \times R(t, t-1)$ is referred to as the first forecasting model on F(t)

The relation F(t-1)→F(t) This is referred to as a fuzzy logical relationship, where F(t-1) represents the current state and F(t) denotes the subsequent state.

Definition 2.1.3[Tsaur R, 2012,385**]**

Suppose that $F(t) = Bi$, occurs as a result of $F(t-1) = Bj$, then the fuzzy logical relationship is expressed as $B_i \rightarrow Bj$.

If multiple fuzzy logical relationships originate from state B_2, leading to various states Bj, j = 1,2, ..., n, for example $B_2 \rightarrow B_3, B_2 \rightarrow B_2, B_2 \rightarrow B_1$; these relationships are then combined to from a fuzzy logical relationship group such as:

$$B_2 \rightarrow B_1, B_2, B_3$$

In general, the construction of a fuzzy time series model involves the following steps: (1) defining the universe of discourse in which the fuzzy set is established (2) partitioning the universe into equally length intervals (3) formulating the fuzzy set B (4) fuzzifying the historical data (5) establishing the fuzzy logical relationships (6) grouping these relationships, and (7) computing the forecasting values.

3. The Algorithm of Chen's Model: [Chen S, 1996,315]

Chen presented an algorithm to simplify the complex calculation process in the Song & Chisum method. The following steps include the algorithm for Chen's model, which can be used to obtain forecasting for the studied fuzzy time series:

I. Definition of the total set S and the interval.
II. The total group is divided into adequate and equal groups.
III. Definition of fuzzy sets.
IV. Each view is assigned to the fuzzy group it belongs to.
V. Extracting logical fuzzy relations and set of logical fuzzy relations.
VI. Prediction.
VII. Removing fuzziness from forecasting by taking the mean.
Forecasting.

The predictive value at time t is determined based on the following rules:

First Rule:

if the current fuzzy set B_i and its set of logical fuzzy relations is an empty set $B_i \rightarrow \Phi$, then the predictive value m_i is the average of the two values S_i.

Second Rule:

If the current fuzzy set B_i and its set of logical fuzzy relations are one-one $B_i \rightarrow B_k$, then the predictive value m_k is the average of the two values S_k.

Third Rule:

If the current fuzzy set B_i and it's set of logical fuzzy relationships are one-many $B_i \rightarrow B_{k1}, B_i \rightarrow B_{k2}, \ldots, B_i \rightarrow B_{kp}$, then the predictive value is calculated according to the following:

$$\frac{\sum_{l}^{p} m_{kl}}{p} \qquad \cdots(2)$$

3.1 Lengths of Intervals [Huarng, K.H.,2001, 391–392**]**

The interval of the fuzzy groups is one of the things that affects the prediction process and has a major impact, as the accuracy of the predicted value changes with the length of the interval. In this research, the Average Based Length method will be applied to identify the interval and the number of fuzzy groups according to the following algorithm:

I. Calculating the absolute value of the first differences of the observations, then calculating mean of the absolute differences.

II. Half the value of the mean is taken as the length.

III. Depending on the length in the previous step, the basis of the length of the span is determined through Table No. (1).

IV. The length is approximated based on the specified basis and adopted as the length of the interval l.

V. The boundaries of the total group are calculated according to the following formula:

$$S = [D_{\min} - D_1, D_{\max} + D_2] \qquad \ldots(3)$$

Whereas:

$D_{\min}$: represents the smallest value in observations.

$D_{\max}$: represents the largest value in observations.

D_1 and D_2 : Numbers chosen to simplify calculations.

VI. The number of fuzzy numbers is calculated according to the following formula:

$$o = \frac{D_{\max} + D_2 - D_{\min} + D_1}{l} \qquad \ldots(4)$$

Table (1) The basis of the length of the span

intervals	value
0.1–1.0	0.1
1.1–10	1
11–100	10
101–1000	100

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1001–10000	1000

4. ARIMA Model:

THE Auto Regressive Integrated Moving Average (ARIMA) model represents time series data using observed value and is widely applied for forecasting future outcomes. When Applied to time series, ARIMA effectively captures patterns in data that are free from random white noise and non-seasonal fluctuations [Filder, T.N.,2019,3]. proposed by Box and Jenkins in 1970. the ARIMA model has demonstrated strong efficiency in generating short-term forecasts, often outperforming more complex structural models [Ariyo, A.,2014, 1-106]. In this approach, the forthcoming value of a variable is expressed as a linear combination of its past values, formulated as follows:

$$Yt = \phi_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \ldots\ldots (5)$$

Yt : represents the actual value.

εt : represents a random error term at t

(ϕ_i , θ_j): These are the coefficients, with p and q being integers commonly known as the autoregressive order and the moving average order, respectively [Areef, 2019, 125].

5. Practical Part:

The data used in this study is cost Importing gasoline in Iraq by USA dollar, period 2013 to 2023. is yearly data in million $, Data obtained through the site https://cosit.gov.iq/ar/,

The initial step taken in forecasting this fuzzy time series BY Chen and predicting by ARIMA (2,0,2) we choice that model because we are testing many models on our data, so ARIMA (2,0,2) has small AME than another models by SPSS, in second step comparing between above two methods by using Absolute Mean Error (AME) shown in table 2.

Table 2 comparing between two methods by using AME

X (million $)	Forecasting by Chen	Predicting by ARIMA
2177.8		1939.6
1845.2	1950	2054.8
1246.1	1500	1734.9
1106.2	1500	1446.4
1444.4	1950	1687.4
1819.6	1500	1931.7
1762.8	1500	1985.6
919.4	1050	1763.7
2543.6	1950	1124.6
3873.9	3750	3275.9

3192.7	3150	2969.7
AME	248.3	470.08

6. Conclusion

While several studies have shown a comparison between ARIMA models and taking the appropriate model in the predicting process using fuzzy time series, they did not address its comparison with forecasting using Algorithm of Chen's Model, because it is necessary to know the difference between predicting and forecasting and which one gives more accurate results and insight, particularly in international business decision-making. This paper showed that the forecasting process using Algorithm of Chen It is better than predicting using ARIMA because it has less AME.

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APPENDIX

The Algorithm of Chen's Model				
The resulting relationship	corresponding fuzzy set	900-3900	X million $	YEAR
A5-A4	A5	U1=(900-1200)	2177.8	2013
A4-A2,A3	A4	U2=(1200-1500)	1845.2	2014
A2-A1,A4	A2	U3=(1500-1800)	1246.1	2015
A1-A2,A6	A1	U4=(1800-2100)	1106.2	2016
A2-A1,A4	A2	U5=(2100-2400)	1444.4	2017
A4-A2,A3	A4	U6=(2400-2700)	1819.6	2018
A3-A1	A3	U7=(2700-3000)	1762.8	2019
A1-A2,A6	A1	U8=(3000-3300)	919.4	2020
A6-A10	A6	U9=(3300-3600)	2543.6	2021
A10-A8	A10	U10=(3600-3900)	3873.9	2022
	A8		3192.7	2023

3900	
3873.9	ax
919.4	min
900	

Model Description

			Model Type
Model ID	x	Model_1	ARIMA(2,0,2)

Model Fit											
Fit Statistic	Mean	SE	Minimum	Maximum	Percentile						
					5	10	25	50	75	90	95
Stationary R-squared	.548	.	.548	.548	.548	.548	.548	.548	.548	.548	.548
R-squared	.548	.	.548	.548	.548	.548	.548	.548	.548	.548	.548
RMSE	786.378	.	786.378	786.378	786.378	786.378	786.378	786.378	786.378	786.378	786.378
MAPE	27.085	.	27.085	27.085	27.085	27.085	27.085	27.085	27.085	27.085	27.085
MaxAPE	91.830	.	91.830	91.830	91.830	91.830	91.830	91.830	91.830	91.830	91.830
MAE	448.990	.	448.990	448.990	448.990	448.990	448.990	448.990	448.990	448.990	448.990
MaxAE	1419.036	.	1419.036	1419.036	1419.036	1419.036	1419.036	1419.036	1419.036	1419.036	1419.036
Normalized BIC	14.425	.	14.425	14.425	14.425	14.425	14.425	14.425	14.425	14.425	14.425

Residual ACF Summary											
Lag	Mean	SE	Minimum	Maximum	Percentile						
					5	10	25	50	75	90	95
Lag 1	.088	.	.088	.088	.088	.088	.088	.088	.088	.088	.088
Lag 2	-.065	.	-.065	-.065	-.065	-.065	-.065	-.065	-.065	-.065	-.065
Lag 3	-.046	.	-.046	-.046	-.046	-.046	-.046	-.046	-.046	-.046	-.046
Lag 4	-.027	.	-.027	-.027	-.027	-.027	-.027	-.027	-.027	-.027	-.027
Lag 5	-.059	.	-.059	-.059	-.059	-.059	-.059	-.059	-.059	-.059	-.059

Lag 6	-.223	.	-.223	-.223	-.223	-.223	-.223	-.223	-.223	-.223	-.223
Lag 7	-.234	.	-.234	-.234	-.234	-.234	-.234	-.234	-.234	-.234	-.234
Lag 8	.027	.	.027	.027	.027	.027	.027	.027	.027	.027	.027
Lag 9	.025	.	.025	.025	.025	.025	.025	.025	.025	.025	.025
Lag 10	.014	.	.014	.014	.014	.014	.014	.014	.014	.014	.014

Residual PACF Summary

Lag	Mean	SE	Minimum	Maximum	Percentile						
					5	10	25	50	75	90	95
Lag 1	.088	.	.088	.088	.088	.088	.088	.088	.088	.088	.088
Lag 2	-.074	.	-.074	-.074	-.074	-.074	-.074	-.074	-.074	-.074	-.074
Lag 3	-.034	.	-.034	-.034	-.034	-.034	-.034	-.034	-.034	-.034	-.034
Lag 4	-.024	.	-.024	-.024	-.024	-.024	-.024	-.024	-.024	-.024	-.024
Lag 5	-.061	.	-.061	-.061	-.061	-.061	-.061	-.061	-.061	-.061	-.061
Lag 6	-.221	.	-.221	-.221	-.221	-.221	-.221	-.221	-.221	-.221	-.221
Lag 7	-.222	.	-.222	-.222	-.222	-.222	-.222	-.222	-.222	-.222	-.222
Lag 8	.015	.	.015	.015	.015	.015	.015	.015	.015	.015	.015
Lag 9	-.041	.	-.041	-.041	-.041	-.041	-.041	-.041	-.041	-.041	-.041
Lag 10	-.026	.	-.026	-.026	-.026	-.026	-.026	-.026	-.026	-.026	-.026

Model Statistics

Model	Number of Predictors	Model Fit statistics				Ljung-Box Q(18)			Number of Outliers
		Stationary R-squared	R-squared	MAPE	MAE	Statistics	DF	Sig.	
x-Model_1	0	.548	.548	27.085	448.990	.	0	.	0

ARIMA Model Parameters

					Estimate	SE	t	Sig.
x-Model_1	x	No Transformation	Constant		1939.641	474.522	4.088	.006
			AR	Lag 1	.237	3.955	.060	.954
				Lag 2	-.456	1.574	-.289	.782
			MA	Lag 1	-.695	4.024	-.173	.869
				Lag 2	-.305	3.854	-.079	.940

Residual ACF

Model		1	2	3	4	5	6	7	8	9	10
x-Model_1	ACF	.088	-.065	-.046	-.027	-.059	-.223	-.234	.027	.025	.014
	SE	.302	.304	.305	.306	.306	.307	.321	.337	.337	.337

Residual PACF											
Model		1	2	3	4	5	6	7	8	9	10
x-Model_1	PACF	.088	-.074	-.034	-.024	-.061	-.221	-.222	.015	-.041	-.026
	SE	.302	.302	.302	.302	.302	.302	.302	.302	.302	.302