Mustard price dynamics due to ban on blending: time series intervention model with nonlinear function

Subhankar Biswas[1], A. K. Paul[2,*], Md Yeasin[2], Ranjit Kumar Paul[2], H. S. Roy[2] and Prakash Kumar[2]

[1]The Graduate School, ICAR-Indian Agricultural Research Institute, New Delhi 110 012, India
[2]ICAR-Indian Agricultural Statistics Research Institute, New Delhi 110 012, India

Intervention analysis is used to study structural changes in data resulting from external events. Traditional time series intervention models, viz. autoregressive integrated moving average model with exogenous variables (ARIMA-X) and artificial neural networks with exogenous variables (ANN-X), rely on linear intervention functions such as step or ramp functions, or their combinations. However, when intervention effects are nonlinear, growth models may offer a viable alternative. This study proposed a new algorithm for time series intervention analysis employing ARIMA and ANN models with a nonlinear intervention function. The Hoerl function has been introduced as a nonlinear intervention function. To demonstrate the effectiveness of the proposed model, monthly wholesale price data from three markets in Rajasthan, namely, Tonk, Alwar and Sriganganagar during January 2010 to May 2023 have been used. The analysis encompassed a comprehensive examination across all markets, revealing that the proposed models consistently outperformed the conventional ARIMA-X and ANN-X methodologies in terms of performance and accuracy.

Keywords: Accuracy, blending, Hoerl model, intervention effect, mustard.

MUSTARD oil holds a prominent position among cooking oils in Asia, particularly in India, owing to its significant medicinal and economic value. Nearly one-third of India's oil production is derived from mustard, making it the country's second most crucial edible oilseed crop following soybean[1]. Renowned for its multifaceted benefits, mustard oil boasts anticarcinogenic properties, aiding in the prevention of cancer cell formation, along with antifungal and antibacterial attributes that contribute to skin disease protection. Additionally, it aids in reducing body temperature, acts as a good appetizer and enhances red blood cell strength[2]. Comprising 37–49% oil content, mustard also contains approximately 1–1.5% minerals and vitamins, 2–3% glucosinolate, 14–15% carbohydrates, 25–30% protein and 10–12% fibre. The composition of mustard oil typically includes around 40–60% erucic acid, 4.5–13% linolenic acid and 25–30% oleic acid[3]. In India, during the 1990s, blending of edible oils was permitted for the first time. This move was prompted by the widespread outbreak of dropsy towards the end of the decade, which was attributed to the adulteration of mustard oil. However, researchers argue that the blending of mustard oil had detrimental effects on both the mustard farming community and public health. Consequently, blending of mustard oil was banned in October 2020. This policy intervention has had repercussions on the price of mustard oil and on the economy of both the farming community and consumers[4].

Time series analysis is used to forecast future events based on the past pattern. The auto regressive integrated moving average (ARIMA) is considered the most notable developed in a class of time series forecasting. This model performs well if the data under consideration is linear and forecast needed is for the short term. But if the past data is affected by intervention, the conventional time series model fails to predict the actual picture of the future. Intervention can be defined as any sudden change in driving force of the variable under study which affects the behaviour or components of the time series data[5]. This change may be educational, administrative and policy interventions, or any natural or unforeseen or man-made events and maybe enforced at the regional, national or continent level.

The time series model with intervention study was proposed by Box and Tiao[6] and further popularized by Larcker *et al.*[7] and Enders *et al.*[8]. Intervention analysis is used to study structural changes in data produced by external events. This intervention study has become popular in different areas including economics, agriculture, medicine and environment. Bianchi *et al.*[9] used the ARIMA model with intervention for the forecasting of telemarketing data. Ismail *et al.*[10] studied the effect of terrorism in the tourism industry of Bali, Indonesia using the ARIMA model with intervention. Arya *et al.*[11] used the autoregressive integrated

*For correspondence. (e-mail: apaul_66@yahoo.com)

moving average with exogenous variables (ARIMA-X) time-series model to model and forecast the pest population. Aboagye-Sarfo *et al.*[12] used an intervention model to study the effect of voluntary counselling and testing (VCT) in the northern and southern sectors of Ghana. Yeasin *et al.*[13] proposed the Generalized Autoregressive Conditional Heteroskedasticity with exogeneous variables (GARCH-X) model with the intervention of exogenous variables and applied it to the data of the domestic price index of edible oil of India. Paul and Birthal[14] studied the effect of COVID-19 intervention on the daily arrivals and wholesale prices of onions, tomatoes and potatoes. Schaffer *et al.*[15] demonstrated the use of the ARIMA model with intervention to quantify the impact of health policy as an intervention. Long *et al.*[16] applied a multi-intervention interrupted time series analysis to estimate the effect of centralized procurement policy on the price of centralized procured international non-proprietary names (INNs) and their alternative INNs. Paul and Yeasin[17] studied the effect of COVID-19 intervention on the price of major pulses in four major markets in India using the GARCH-X model. Prabhakar *et al.*[18] studied the influence of weather factors lagged by one week on soybean semilooper (*Chrysodeixis acuta*) pest status using a hybrid of ARIMAX and Artificial Neural Network (ANN). Rathod *et al.*[19] studied the effect of COVID-19 on the prices of rice in India using the ARIMA model, ARIMA with Intervention, ANN, ANN with Intervention, the extreme learning machine (ELM) model and ELM with Intervention. Xie *et al.*[20] proposed a multi-variable hybrid attentive model (MVHA) by jointly mining multiple time series to predict the forthcoming need for intravenous injections to the patients of intensive care units. Zhang *et al.*[21] introduced a robust technique for the time series intervention model by using least squares and the bootstrap method. Zhao *et al.*[22] conducted a study using the seasonal autoregressive integrated moving average intervention (SARIMA-Intervention) model to study the relationship between the monthly HIV cases and COVID-19 policy intervention in China.

In many of these studies, the intervention function employed typically consists of a step or ramp function, or a combination thereof, which is linear. However, when the intervention effect exhibits nonlinearity, growth models can also serve as suitable intervention functions. Numerous growth models found in the literature have been dedicated to studying and predicting the nonlinear patterns of time series[23,24]. In this particular study, a new algorithm is proposed for time series intervention analysis, utilizing ARIMA and ANN models with nonlinear intervention functions. To demonstrate the effectiveness of the algorithm, it is applied to analyse the intervention of the ban on blending mustard oil in October 2020 for the production of multi-sourced edible vegetable oils (MSEVOs) by the Food Safety and Standards Authority of India (FSSAI).

Materials and methods

Time series model

The time series model employs the lagged variable as the independent variable. Several time series models have been developed in the literature based on the nature of time series data. Notably, the ARIMA and ANN models stand out as two important models in time series analysis.

ARIMA model

One of the popular linear time series models is ARIMA[25], which was developed in the 1970s by Box and Jenkins[26]. The ARIMA model is composed of AR and MA models with a combination of integrated terms. An ARIMA (p, d, q) model can be represented as

$$\varphi(B)(1-B)^d Y_t = \theta(B)\varepsilon_t, \qquad (1)$$

where B is the backward shift operator defined as $B(Y_t) = Y_{t-1}$ and $B^i(Y_t) = Y_{t-i}$

$$\varphi(B) = (1-\varphi_1 B - \varphi_2 B^2 - \cdots - \varphi_p B^p),$$

$$\theta(B) = (1-\theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q),$$

$(1 - B)^d$ is the dth order differencing operator to produce the stationarity of the dth order differenced data.

ANN model

ANN model is an effective alternative model for forecasting nonlinear time series data[27]. The ANN imitates human intelligence by processing information in three layers, such as input, hidden and output layers. The feed-forward architecture with back propagation optimization is one of the popular ANN types used for time series data. An ANN model can be represented by the following equation

$$Y_t = a_0 + \sum_{j=1}^{q}\left(a_j g\left(b_{0j} + \sum_{i=1}^{p}(b_{ij} y_{t-p}) + \varepsilon_t\right)\right), \qquad (2)$$

where a_j, b_{ij} are synopsis weight, p the number of hidden nodes represented in terms of a number of lags, q the number of hidden nodes and g is the activation function.

Time series with intervention model

If there are any intervention effects in time series data, the traditional time series model fails to capture behaviour within the data. The time series with intervention model came into existence to cope with the drawback of the traditional time series model. The intervention can be incorporated into the model using a dummy as an exogenous variable. External factors, known as exogenous variables, may affect the target variable even though they are not influenced by the model. ARIMA-X and ANN-X are two important time series with intervention models which have been utilized in this study.

ARIMA-X model

Autoregressive integrated moving average with exogenous inputs is known as the ARIMA-X model[28]. ARIMA-X is the generalization of ARIMA where an exogenous variable is incorporated into the ARIMA model to study the effect of that exogenous variable[29]. An ARIMA-X model can be represented as

$$\left(1-\sum_{s=1}^{p}\alpha_s B^s\right)\Delta Y_t = \mu + \sum_{i=1}^{k}\beta_i' x_{t,i} + \left(1+\sum_{s=1}^{q}\gamma_s B^s\right)\varepsilon_t, \quad (3)$$

where $\Delta Y_t = Y_t - Y_{t-1}$, $B^s = Y_{t-s}$, $\mu \in R$, $\alpha_s \in R$, $\beta_i \in R$, $\gamma_s \in R$ are unknown parameters. The ε_t represents the error terms, p, q and k are parameters specified in advance.

ANN-X

Similar to ARIMA-X, the ANN-X model can be developed by incorporating exogenous variables in the ANN model. It is a generalization of the ANN model with an exogenous variable. By adding exogenous variables in the ANN model, it can handle the intervention data that helps in improving the prediction accuracy of the model. The ANN-X structure can be visualized in Figure 1.

Intervention function

Intervention function is the mathematical representation of the exogenous variable included in the study. Depending on the nature and behaviour of the intervention effect, the intervention function can have a different mathematical form.

Step function

Following an intervention, the time series undergoes an immediate and continuous shift, either upward or downward by a specified magnitude. Prior to the intervention, the step change variable holds a value of 0, transitioning to 1 upon the commencement of the intervention. The step function is represented mathematically as

$$S_t = \begin{cases} 0, & \text{if } t < T_0 \\ 1, & \text{if } t \geq T_0 \end{cases}, \quad (4)$$

where T_0 is the point of intervention.

Pulse or point function

A sudden, temporary change, which is observed at one or more time points immediately following an intervention, and subsequently returns to its baseline level. The pulse variable assumes a value of 1 on the day of the intervention, reverting to 0 otherwise. Mathematically, the pulse function is represented as

$$P_t = \begin{cases} 0, & \text{if } t \neq T_0 \\ 1, & \text{if } t = T_0 \end{cases}. \quad (5)$$

Ramp function

In the ramp function, following the intervention, an immediate alteration in slope takes place. Prior to the onset of the intervention, the ramp variable maintains a value of 0, subsequently incrementing by 1 after the intervention date. The ramp function is mathematically represented as

$$R_t = \begin{cases} 0, & \text{if } t < T_0 \\ t - T_0 + 1, & \text{if } t \geq T_0 \end{cases}. \quad (6)$$

Proposed methodology

In the existing literature on time series model with intervention analysis, the use of ARIMA-X and ANN-X incorporating *X* as an exogenous variable have been mentioned where the intervention function is in linear for such as pulse, step or ramp function. But in real data, the intervention effect is not always linear. In this study, the nonlinear effect of the intervention has been incorporated in the time series model using growth models.

The nonlinear growth model is a mathematical framework used to describe the growth or change of a variable over time in a nonlinear way. It is often employed in fields

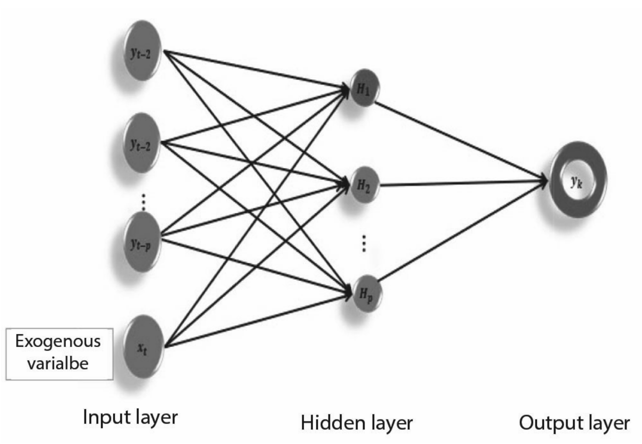

Figure 1. Schematic presentation of artificial neural network with exogenous variables (ANN-X) model.

such as statistics, economics and biology to model complex growth patterns that cannot be adequately captured by linear models. Unlike linear models, which assume a constant rate of change over time, the nonlinear growth model allows for more flexible and realistic representation of growth dynamics. There are a number of nonlinear models present in the literature such as the exponential growth model, the logistic growth model, the Gompertz growth model, Richards's growth model, the Hoerl model, etc.

In this study, the Hoerl model has been selected and implemented. The choice between the Hoerl growth model and other nonlinear models is due to several factors, including the specific characteristics of the data and the research objectives. One reason to opt for the Hoerl growth model is its greater flexibility in capturing diverse growth patterns. While the common model assumes a sigmoidal growth curve with a clear saturation point, the Hoerl model offers more variability in shape and dynamics, allowing for a better fit to data that may exhibit complex or irregular growth trajectories. Additionally, the Hoerl model may be preferred when there is uncertainty about the underlying growth process or when there are multiple potential factors influencing growth that need to be accounted for simultaneously. Its versatility and adaptability make the Hoerl growth model a valuable choice to accurately model and understand nonlinear phenomena in various fields. Mathematically Hoerl model is represented as

$$H_t = ab^t t^c. \tag{7}$$

This is a combination of exponential and power functions, where H_t represents the value of the residual of the study variable at time t, b^t represents an exponential growth or decay factor and t^c represents a power term. a is the scaling parameter or the initial value of the function, b controls the exponential growth (or decay) rate and c controls the growth (or decay) rate of the power function. The constants a, b and c determine how the function behaves with different t values.

Utilizing the Hoerl nonlinear model as a foundation, ARIMA-X and ANN-X models with nonlinear intervention have been proposed. In the case of the time series model featuring nonlinear intervention, initial fitting of ARIMA/ANN models has been conducted using pre-intervention data. Subsequently, leveraging the best-fitted ARIMA/ANN models, predictions were computed for the post-intervention period. Following this, residuals were computed, and various nonlinear growth models were applied to these residuals. Among these models, the nonlinear Hoerl model emerged as the best fit for the residuals in this study. Consequently, a new approach was adopted, incorporating nonlinear growth models as intervention functions. The resulting nonlinear model for the post-intervention period was then combined with the forecast from ARIMA/ANN for the same period. The methodology has been outlined in Figure 2.

Forecasting performance

To compare the performance of the developed model with the existing model, mainly two approaches are followed, viz. mean absolute percentage error (MAPE) and root mean squared error (RMSE).

The MAPE is represented by

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{(Y_t - \hat{Y}_t)}{Y_t}\right| \times 100\%. \tag{8}$$

The RMSE is represented by

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_t - \hat{Y}_t)^2}, \tag{9}$$

where n represents the total number of observations, Y_t the actual value at time t and $\hat{Y}_t$ represents the estimated value at time t.

Result and discussion

The monthly wholesale price (Rs/quintal) of mustard from January 2010 to May 2023 has been collected from three major markets in Rajasthan, namely, Tonk, Alwar and Sriganganagar from AGMARKNET portal (https://agmarknet.gov.in/). Rajasthan is one of the major mustard-producing states, contributing approximately 43% of overall production. Each market has 161 data points, of which the initial 129 data points represent the period prior to the intervention (before October 2020) and the remaining 32 data points correspond to the post-intervention phase.

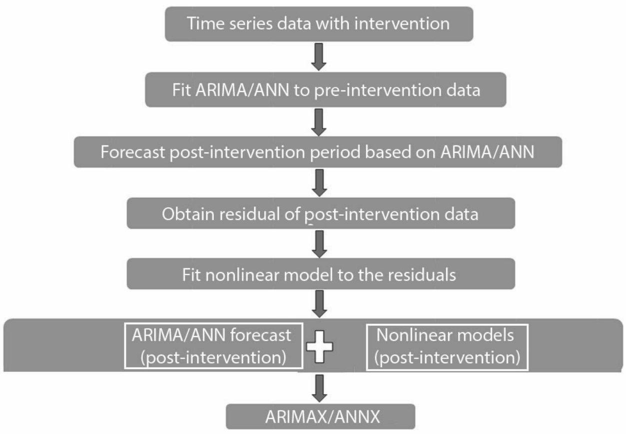

Figure 2. Flowchart of the proposed model.

Table 1. Descriptive statistics of different markets

Statistics	Alwar market	Tonk market	Sriganganagar market
Mean	4041.89	3820.44	3944.79
Median	3760.60	3637.94	3657.47
Standard deviation	1284.03	1584.11	1263.80
Kurtosis	0.70	1.20	0.54
Skewness	1.11	–0.27	1.08
Range	5335.42	7486.60	5084.55
CV (%)	31.77	41.46	32.04
Minimum	2125.47	2196.21	2138.44
Maximum	7460.89	7486.60	7222.99

Table 2. Stationarity test and appropriate differencing

	Augmented Dickey–Fuller (ADF) test				Phillips–Perron (PP) test			
	Original		First differenced		Original		First differenced	
Markets	*t*-statistic	*P*-value	*t*-statistic	*P*-value	*t*-statistic	*P*-value	*t*-statistic	*P*-value
Alwar	–2.87	0.21	–4.73	<0.01	–2.48	0.37	–69.57	<0.01
Tonk	–2.47	0.37	–3.80	0.02	–10.51	0.50	–73.55	<0.01
Sriganganagar	–2.70	0.28	–5.14	<0.01	–13.26	0.35	–94.97	<0.01

Table 3. Best-fitted autoregressive integrated moving average (ARIMA) for different markets

		Parameters				Box-Pierce test	
Market	Model	MA 1	MA 2	MA 3	AIC	Test statistic	*P*-value
Alwar	ARIMA (0, 1, 3)	0.434 (0.092)	0.217 (0.108)	–0.183 (0.092)	1639.03	0.002	0.962
Tonk	ARIMA (0, 1, 1)	0.392 (0.072)			1579.73	0.029	0.864
Sriganganagar	ARIMA (0, 1, 2)	0.252 (0.091)	–0.085 (0.111)		1671.25	0.027	0.868

AIC, Akaike information criterion. The standard error has been given in ‘()’.

Table 4. Parameters estimate of Hoerl model for ARIMA residuals

Market	Parameter	Estimate	*P*-value	R^2	Adjusted R^2
Alwar	*a*	3.188	0.351	0.807	0.793
	b	0.723	<0.001		
	c	4.316	<0.001		
Tonk	*a*	2.036	0.320	0.843	0.832
	b	0.719	<0.001		
	c	4.428	<0.001		
Sriganganagar	*a*	5.707	0.209	0.862	0.853
	b	0.754	<0.001		
	c	3.779	<0.001		

Table 1 indicates that the highest mean price for the mustard quantity is in the Alwar market (Rs 4041.89/quintal) and the lowest mean price is in the Tonk market (Rs 3820.44/quintal). The kurtosis for all the markets represents that the markets are platykurtic in nature, the coefficient of variation of the markets ranges from 31.76% to 41.46%.

Prior to the implementation of the ARIMA model, the stationarity of the series was assessed using the augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test. The null hypothesis for both the ADF test and the PP test is that the time series data has a unit root, indicating that it is non-stationary. In other words, the null hypothesis suggests that the series possesses a stochastic trend and lacks stationarity. The findings are summarized in Table 2.

The results indicated that all series were initially non-stationary but achieved stationarity after the first differentiation.

To preliminarily select the order of the ARIMA model, the autocorrelation function (ACF) and partial autocorrelation function (PACF) were consulted. Subsequently, the best model was chosen based on the Akaike information criterion (AIC)[30] and Bayesian information criterion (BIC)[31]. Diagnostic checking of the best-fitted ARIMA model was conducted using the Box-Pierce test on the residuals.

Table 5. Parameters estimate of Hoerl model for artificial neural network (ANN) residuals

Market	Parameter	Estimate	*P*-value	R^2	Adjusted R^2
Alwar	*a*	197.908	<0.01	0.903	0.896
	b	0.859	<0.01		
	c	1.918	<0.01		
Tonk	*a*	106.101	0.005	0.919	0.914
	b	0.829	<0.01		
	c	2.361	<0.01		
Sriganganagar	*a*	205.480	<0.01	0.807	0.793
	b	0.861	<0.01		
	c	1.869	<0.01		

Table 6. Comparison of the existing and proposed model using ARIMA

	ARIMA with step function		ARIMA with ramp function		ARIMA with (step + ramp) function		Proposed model	
Market	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
Alwar	419.34	5.48	419.77	5.51	419.35	5.48	382.17	5.302
Tonk	357.18	4.64	357.80	4.67	357.03	4.63	326.92	4.473
Sriganganagar	314.29	4.53	311.74	4.37	314.03	4.52	294.89	3.935

RMSE, Root mean squared error; MAPE, Mean absolute percentage error.

Table 7. Comparison of the existing and proposed model using ANN

	Proposed model		ANN with intervention	
Market	RMSE	MAPE	RMSE	MAPE
Alwar	328.53	4.09	348.93	4.29
Tonk	341.37	4.71	347.53	4.79
Sriganganagar	240.46	3.32	319.63	4.43

The null hypothesis for the Box-Pierce test posits that the residuals are independently distributed. Table 3 indicates that the model fits the data well. The estimated parameters and the corresponding AIC values for the best-fitted ARIMA models for the three markets, along with the results of the Box-Pierce test, are also summarized in Table 3. The ANN has been fitted using the optimization of various parameters and hyper-parameters.

Following the development of ARIMA and ANN models, forecasted values for the post-intervention period have been obtained, and residuals were subsequently calculated. These residuals were then fitted using various nonlinear estimation techniques. Models including the exponential model, modified exponential model, logistic model, Gompertz model, monomolecular model, Richard's model and Hoerl model were applied to the residuals of both ARIMA and ANN forecasts. These models were evaluated using R^2 and adjusted R^2 statistics. Across all data series, the Hoerl model emerged as the best-fitted model for both ARIMA and ANN residuals. Table 4 shows the parameters of the best-fitted Hoerl model and Table 5 shows the residual ARIMA and ANN respectively, along with their corresponding R^2 and adjusted R^2 values.

From Tables 4 and 5, it is evident that the Hoerl model demonstrates R^2 value exceeding 80% and 90% across different markets, suggesting a well-fitted model for the residual series.

In the traditional approach, intervention analysis has been conducted using step function, ramp function and their amalgamation. To assess the performance of the proposed model against the existing one, we have tabulated the MAPE and RMSE values in Tables 6 and 7 respectively.

The comparison reveals that the proposed ARIMA-based model outperforms the conventional intervention analysis method across all existing combinations of pulse and ramp functions, as indicated by lower RMSE and MAPE values for all three markets. Similarly, it is evident from Table 7 that the proposed model with ANN surpasses the performance of the conventional intervention analysis model. The actual and predicted plot of Hoerl model and the proposed model have been shown in Figures 3 and 4 respectively.

Conclusion

Intervention analysis plays a pivotal role in understanding the significant impact of interventions both in the present and future contexts. Interventions are the main cause of inducing a sudden behavioural change in specific time series. While various established methods exist for studying intervention effects, historically, researchers have primarily relied on step functions, ramp functions, or a combination of both, i.e. linear intervention function for incorporating intervention in a time series model. In the present study, a new approach for analysing intervention effects in time series data has been proposed using ARIMA and ANN with nonlinear growth models. To illustrate the proposed model, monthly price data from three major markets of

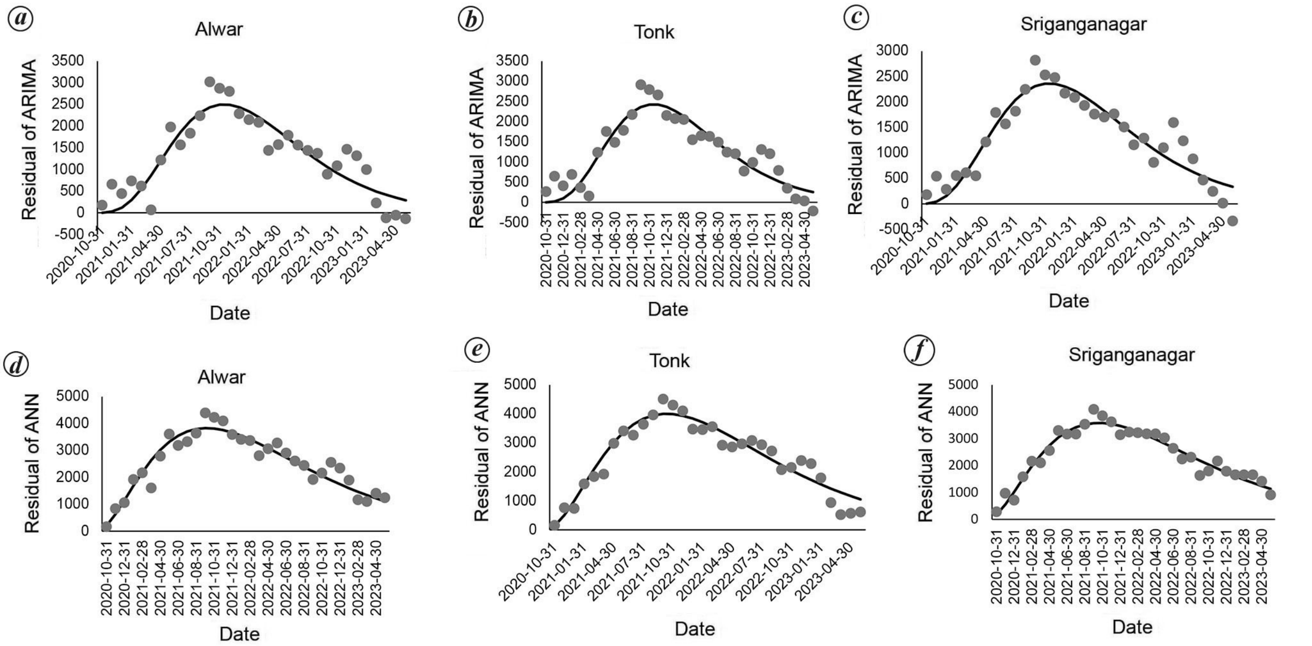

Figure 3. Actual and fitted plot of Hoerl model on the residuals of ARIMA (***a***, ***b*** and ***c***) and ANN (***d***, ***e*** and ***f***) forecast for different markets.

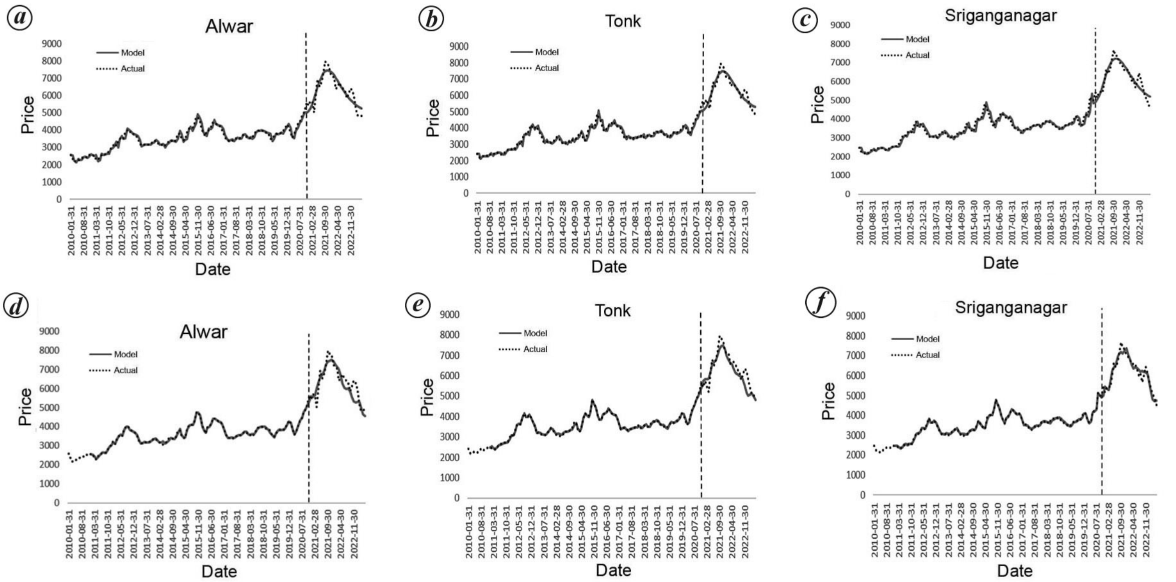

Figure 4. Actual and fitted plots for different markets of proposed models, ARIMA-X (***a***, ***b*** and ***c***) and ANN-X (***d***, ***e*** and ***f***) with nonlinear intervention.

mustard have been used. Across all markets, the proposed models exhibited superior performance compared to the existing methodologies. Specifically, when comparing the pre-intervention period, the proposed intervention models outperformed existing ARIMA with intervention models and ANN with intervention models utilizing step, ramp or combined functions. Notably, within the same market, the model employing ANN demonstrated superior performance over the model utilizing ARIMA. The future scope lies in exploring the application of advanced machine learning techniques and deep learning models for more precise intervention analysis in diverse datasets. Additionally, integrating real-time data and incorporating dynamic modelling frameworks could further enhance the effectiveness of intervention analysis in addressing contemporary socio-economic challenges.

Conflict of interest: The authors declare no conflict of interest.

1. Layek, N., Mula, G., Sarkar, A. and Roy, B., Economics of mustard seed production – an analytical study from Terai Zone of West Bengal. *Indian J. Ext. Educ.*, 2021, **57**(2), 78–85.

2. Kaur, R., Sharma, A. K., Rani, R., Mawlong, I. and Rai, P. K., Medicinal qualities of mustard oil and its role in human health against chronic diseases: a review. *Asian J. Dairy Food Res.*, 2019, **38**(2), 98–104.
3. Chavan, N. R., Karpe, P. J. and Jadhav, S. S., Influence of different nutrient sources on seed and oil yield and economics of mustard (*Brassica juncea*). *Pharma Innov. J.*, 2021, **10**(12), 1588–1590.
4. Ray, M., Kumar, A. and Srivastava, S. K., The impact of policy changes on the mustard ecosystem: a multi-stakeholder perspective. *J. Agribusiness Dev. Emerg. Econ.*, 2023; https://doi.org/10.1108/JADEE-12-2022-0270.
5. Lam, C. Y., Ip, W. H. and Lau, C. W., A business process activity model and performance measurement using a time series ARIMA intervention analysis. *Exp. Syst. Appl.*, 2009, **36**(3), 6986–6994.
6. Box, G. E. P. and Tiao, G. C., Intervention analysis with applications to economic and environmental problems. *J. Am. Stat. Assoc.*, 1975, **70**(349), 70–79.
7. Larcker, D. F., Gordon, L. A. and Pinches, G. E., Testing for market efficiency: a comparison of the cumulative average residual methodology and intervention analysis. *J. Fin. Quantit. Anal.*, 1980, **15**(2), 267–287.
8. Enders, W., Sandler, T. and Parise, G. F., An econometric analysis of the impact of terrorism on tourism. *Kyklos*, 1992, **45**(4), 531–554.
9. Bianchi, L., Jarrett, J. and Hanumara, R. C., Improving forecasting for telemarketing centers by ARIMA modeling with intervention. *Int. J. Forecast.*, 1998, **14**(4), 497–504.
10. Ismail, Z., Suhartono, Yahaya, A. and Efendi, R., Intervention model for analyzing the impact of terrorism to tourism industry. *J. Math. Stat.*, 2009, **5**(4), 322–329.
11. Arya, P., Paul, R. K., Kumar, A., Singh, K. N., Sivaramne, N. and Chaudhary, P., Predicting pest population using weather variables an ARIMAX time series framework. *Int. J. Agric. Stat. Sci.*, 2015, **11**(2), 381–386.
12. Aboagye-Sarfo, P., Cross, J. and Mueller, U., Intervention time series analysis of voluntary, counselling and testing on HIV infections in West African sub-region: the case of Ghana. *J. Appl. Stat.*, 2017, **44**(4), 571–582.
13. Yeasin, M., Singh, K. N., Lama, A. and Paul, R. K., Modelling volatility influenced by exogenous factors using an improved GARCH-X model. *J. Indian Soc. Agric. Stat.*, 2020, **74**(3), 209–216.
14. Paul, R. K. and Birthal, P. S., The prices of perishable food commodities in India: the impact of the lockdown. *Agric. Econ. Res. Rev.*, 2021, **34**(2), 151–164.
15. Schaffer, A. L., Dobbins, T. A. and Pearson, S. A., Interrupted time series analysis using autoregressive integrated moving average (ARIMA) models: a guide for evaluating large-scale health interventions. *BMC Med. Res. Methodol.*, 2021, **21**(1), 1–12.
16. Long, H., Yang, Y., Geng, X., Mao, Z. and Mao, Z., Changing characteristics of pharmaceutical prices in China under centralized procurement policy: a multi-intervention interrupted time series. *Front. Pharmacol.*, 2022, **13**, 944540.
17. Paul, R. K. and Yeasin, M., COVID-19 and prices of pulses in major markets of India: impact of nationwide lockdown. *PLoS ONE*, 2022, **17**(8), e0272999.
18. Prabhakar, M., Vennila, S., Prasad, Y. G., Kumar, G. S., Paul, R. K. and Yadav, S. K., ARIMAX – artificial neural network hybrid model for predicting semilooper (*Chrysodeixis acuta*) incidence on soybean. *Int. J. Trop. Insect Sci.*, 2022, **42**(5), 3601–3608.
19. Rathod, S., Chitikela, G., Bandumula, N., Ondrasek, G., Ravichandran, S. and Sundaram, R. M., Modeling and forecasting of rice prices in India during the COVID-19 lockdown using machine learning approaches. *Agronomy*, 2022, **12**(9), 2133.
20. Xie, J., Wang, Z., Yu, Z. and Guo, B., Enabling timely medical intervention by exploring health-related multivariate time series with a hybrid attentive model. *Sensors*, 2022, **22**(16), 6104.
21. Zhang, S., McKean, J. W. and Huitema, B. E., Least squares and robust rank-based double bootstrap analyses for time-series intervention designs. *Evaluat. Health Profess.*, 2022, **45**(4), 362–376.
22. Zhao, T., Liu, H., Bulloch, G., Jiang, Z., Cao, Z. and Wu, Z., The influence of the COVID-19 pandemic on identifying HIV/AIDS cases in China: an interrupted time series study. *Lancet Reg. Health West. Pac.*, 2023; https://doi.org/10.1016/j.lanwpc.2023.100755.
23. Chary, D. S., Supriya, K., Anjaiah, T., Meena, A. and Ramesh, M., Trends in fertilizer nutrients (N, P_2O_5 and K_2O) consumption in India. *Biol. Forum – an Int. J.*, 2023, **15**(6), 690–696.
24. Sanju and Singh, D., Non-linear growth models for acreage, production and productivity of food-grains in Haryana. *J. Exp. Agric. Int.*, 2023, **45**(7), 1–8.
25. Peter, D. and Silvia, P., ARIMA vs ARIMAX – which approach is better to analyze and forecast macroeconomic time series. In Proceedings of 30th International Conference Mathematical Methods in Economics, 2012, vol. 2, pp. 136–140.
26. Makridakis, S. and Hibon, M., ARIMA models and the Box-Jenkins methodology. *J. Forecast.*, 1997, **16**(3), 147–163.
27. Zhang, G., Patuwo, B. E. and Hu, M. Y., Forecasting with artificial neural networks: the state of the art. *Int. J. Forecast.*, 1998, **14**(1), 35–62.
28. Kour, S., Shitap, M. S., Pradhan, U. K., Paul, R. K., Arya, P. and Kumar, A., Forecasting of rice yield based on weather parameters in Kheda district of Gujarat, India. *Int. J. Agric. Stat. Sci.*, 2018, **14**(2), 611–615.
29. Paul, R. K., Vennila, S., Singh, N., Chandra, P., Yadav, S. K., Sharma, O. P. and Prabhakar, M., Seasonal dynamics of sterility mosaic of pigeonpea and its prediction using statistical models for Banaskantha region of Gujarat, India. *J. Indian Soc. Agric. Stat.*, 2018, **72**(3), 213–223.
30. Akaike, H., A new look at the statistical model identification. *IEEE Trans. Automatic Control*, 1974, **19**(6), 716–723.
31. Schwarz, G., Estimating the dimension of a model. *Ann. Stat.*, 1978, **6**(2), 461–464.
32. Abonazel, M. R. and Abd-Elftah, A. I., Forecasting Egyptian GDP using ARIMA models. *Rep. Econ. Finance*, 2019, **5**(1), 35–47.
33. Jha, A. and Saha, D., Forecasting and analysing the characteristics of 3G and 4G mobile broadband diffusion in India: a comparative evaluation of Bass, Norton-Bass, Gompertz, and logistic growth models. *Technol. Forecast. Soc. Change*, 2020, **152**, 119885.
34. Paul, R. K. and Sinha, K., Forecasting crop yield: a comparative assessment of ARIMAX and NARX model. *Rashi*, 2016, **1**(1), 77–85.
35. Poddar, K. H., Sikand, G., Kalra, D., Wong, N. and Duell, P. B., Mustard oil and cardiovascular health: why the controversy? *J. Clin. Lipidol.*, 2022, **16**(1), 13–22.
36. Rana, Q. U. A., Irfan, M., Ahmed, S., Hasan, F., Shah, A. A., Khan, S. and Badshah, M., Bio-catalytic transesterification of mustard oil for biodiesel production. *Biofuels*, 2022, **13**(1), 69–76.
37. Sarkar, A. and Kartikeyan, B., Intervention analysis with nonlinear dependent noise variation. *Stat. Probab. Lett.*, 1993, **18**(2), 91–103.

ACKNOWLEDGEMENT. We thank the Graduate School Indian Agricultural Research Institute and ICAR-Indian Agricultural Statistics Research Institute, New Delhi for support.

Received 20 March 2024; revised accepted 30 August 2024

doi: 10.18520/cs/v127/i10/1233-1240