Artificial intelligence methods for oil price forecasting: a review and evaluation

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Neha Mehra
O.P. Jindal Global University

Krishan K Pandey
O.P. Jindal Global University

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Artificial intelligence methods for oil price forecasting: a review and evaluation

Neha Sehgal[1] · **Krishan K. Pandey**[2]

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Abstract Artificial intelligent methods are being extensively used for oil price forecasting as an alternate approach to conventional techniques. There has been a whole spectrum of artificial intelligent techniques to overcome the difficulties of complexity and irregularity in oil price series. The potential of AI as a design tool for oil price forecasting has been reviewed in this study. The following price forecasting techniques have been covered: (i) artificial neural network, (ii) support vector machine, (iii) wavelet, (iv) genetic algorithm, and (v) hybrid systems. In order to investigate the state of artificial intelligent models for oil price forecasting, thirty five research papers (published during 2001 to 2013) had been reviewed in form of table (for ease of comparison) based on the following parameters: (a) input variables, (b) input variables selection method, (c) data characteristics (d) forecasting accuracy and (e) model architecture. This review reveals procedure of AI methods used in complex oil price related studies. The review further extended above overview into discussions regarding specific shortcomings that are associated with feature selection for designing input vector, and then concluded with future insight on improving the current state-of-the-art technology.

Keywords Neural networks · Feature selection · Support vector machine · Hybrid systems · Oil price forecasting

✉ Krishan K. Pandey
krishan.pandey@gmail.com

Neha Sehgal
nmehra@jgu.edu.in

1 Jindal Global Business School, O. P. Jindal Global University, Sonipat Narela Road, Near Jagdishpur Village, Sonipat, Sonipat, Haryana 131001, NCR of Delhi, India

2 College of Management and Economic Studies, University of Petroleum and Energy Studies, Energy Acres, P.O. Bidholi, Via-Prem Nagar, Dehradun 248007, India

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List of symbols

R^2	Coefficient of determination
A	Annual
AC	Analog complexity
ACF	Auto-correlation function
ACIX	Autoregressive conditional interval model with exogenous explanatory interval variable
AE	Absolute error
AI	Artificial intelligent
ALNN	Adaptive linear neural network
AMIN	AI framework of Amin-Naseri et al.
ANN	Artificial Neural Network
APARCH	Asymmetric power ARCH
AR	Annualised return
ARIMA	Autoregressive integrated moving average
BFGS	Broyden–Fletcher–Goldfarb–Shanno–Quasi Newton
BiP Sig	Bipolar sigmoid
BLR	Bias learning rule
BNN	Boltzmann Neural Network
BP	Back-propagation
BPNN	Back-Propagation Neural Network
BR	Bayesian regulation
Br	Brent crude oil market
BVaR	Bayesian vector auto-regression
CA	Correlation analysis
Ca-Var	Conditionally autoregressive VaR
CC	Cluster classifier
CrI	Crisis index
D	Daily
DA	Day ahead
Db	Daubechies
DirS	Direct strategy
DNN	Decomposition based Neural Networks
DS	Directional statistics
DT	Delta test
Du	Dubai oil market
ECM	Error correction model
EGARCH	Exponential GARCH
EM	Expectation maximization
EMD	Empirical mode decomposition
ENN	Elman Neural Network
FBS	Forward backward selection
FIGARCH	Fractionally integrated GARCH
FIML	Full information maximum likelihood
FLNN	Functional Link Neural Network

FM	Fuzzy model
FNN	Fuzzy Neural Network
FP	NYMEX future prices
GA	Genetic Algorithm
GARCH	Generalized autoregressive conditional heteroskedasticity
GB	Geometric Brownian process
GD	Gradient descent
GDX	Gradient descent BEP
GPMGA	Generalized Pattern Matching Genetic Algorithm
GRNN	General Regression Neural Network
GSM	Grey system model
GT	Gamma test
HaT	Harr a Trous
HM	Hidden Markov Model
HQIC	Hannan–Quinn info criterion
HR	Hit rate
HTS	Hyperbolic tangent sigmoid
HWBT	Hull white with binomial tree
IBL	Instance based learning
IGARCH	Integrated GARCH
IGP	Inverse Gaussian process
JC	Judgemental criterion
KAB	Genetic Programming framework of Kaboudan
L-RIM	Linear relative inventory model
LD	Log-differenced
Lgs	Logistic
LM	Levenberg–Marquardt Algorithm
LS	Logarithmic sigmoid
LSE	Least Square Error
M	Monthly
MA	Month ahead
MAE	Mean Absolute Error
MAPE	Mean absolute percentage error
MFA	Manual feature extraction
MLP	Multi-layered Feed Forward Neural Network
MoGNN	Mixture of Gaussian NN
MRP	Mean reverting process
MSE	Mean Squared Error
NL-RIM	Non-linear relative inventory model
NMSE	Normalised Mean Squared Error
NN	Neural networks
NORM	Normalization
NRW	Naïve random walk
NSR	Noise-to-signal ratio
OLS	Ordinary Least Square
OU	Ornstein–Uhlenbeck Model

PACF	Partial autocorrelation function
PARCH	Power ARCH
PCP	Percentage of correct predictions
PGRP	Persian Gulf region prices
PMI	Partial mutual information
PR	Prediction rate
PRMS	Pattern modelling in recognition system approach
RBF	Radial basis function
RecS	Recursive strategy
RM	Regression model
RMA	Relative change of moving average
RMS	Regime Markov switching stochastic volatility model
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
RS	Regime switching
RT	Return transformation
RW	Random walk
S-SVM	Standard SVM
SA	Step ahead
Sig	Sigmoid
SM	Stochastic model
SMAPE	Symmetric MAPE
SMP	Smoothing procedure
SNR	Signal-to-noise ratio
SoMLP	Self-organizing MLP
SP	Spot prices
SR	Scaling range
SSE	Sum of Square Error
STEO	EIA's short-term energy outlook econometric model
SVM	Support vector machine
SVR	Support vector regression
TE	Trial and error method
TGARCH	Threshold GARCH
TM	Text mining
TPA	Time period ahead
TSig	Tangent sigmoid
TSK	Takagi–Sugano–Kang
VaR	Value-at-risk model
VECM	Vector error correction model
W	Weekly
WA	Week ahead
WANG	AI framework of Wang et al.
WCI	Without crisis index
WDE	Wavelet decomposition ensemble
WNN	Wavelet Neural Network
WSP	Without smoothing procedure

WT	Wavelet transform
WTI	West Texas Intermediate Crude Oil Market

1 Introduction

Fossil fuels currently account for 87 % of primary energy demand and projected to still make up 82 % of the global total by 2035. According to BP [1], oil remains the world's primary fuel, accounting to 33.1 % of global energy consumptions. Oil will remain the energy type with the largest share for most of the projected periods and will continue to play a foremost part in satisfying world energy needs [2]. Oil price act as a key component dominating investment picture for years to come on. They act as a key variable in evaluation of economic development, energy policy decisions and stock markets [1]. A prior knowledge of oil prices fluctuations helps oil producers to make decisions about the increase or decrease in production levels accordingly.

Oil prices helps strategically in macroeconomic projections and macroeconomic risk analysis for central and private banks. They are helpful in predicting recession in business cycles [3]. They are helpful in planning regulatory policies regarding taxes & standards. Businesses dependent on oil will be benefited as they will be in position to take measures to control manufacturing and sales of their products in line with expected trend of forecast oil prices. Accurate forecasting helps Non-OPEC countries to take effective measures so their growth remains robust and thus benefited consumers. Further, economic policies can be formulated in way to overcome recession and unemployment.

2 Econometric models

Forecasting of crude oil prices is an important task for better investment management, macroeconomic policies and risk management. It is important to analyses the probabilistic assumption of oil prices in terms of normality, linearity and serial correlation [4]. To forecast crude oil prices, a variety of approaches have been proposed by numerous authors employing time series [5–10], financial models [11,12] and structural models [13–18].

2.1 Time series model

Time series analysis is a method of forecasting that focuses on the historical behaviour of dependant variable. Oil prices are assumed to be normally distributed in many studies but their departure from normal distribution was disregarded due to misinterpretation of Central Limit Theorem [4,19]. Crude oil prices are found to be non Gaussian. Forecasting crude oil prices through fundamental method is a complex task due to uncertainty, noisiness and non-stationary inbuilt in indicators that drive them. Therefore, time series models provide an alternative to analyse and predict future movements based on past behaviour of oil prices [20]. The price-forecasting models based on time-series approach have been further classified into three subsets as shown in Fig. 1.

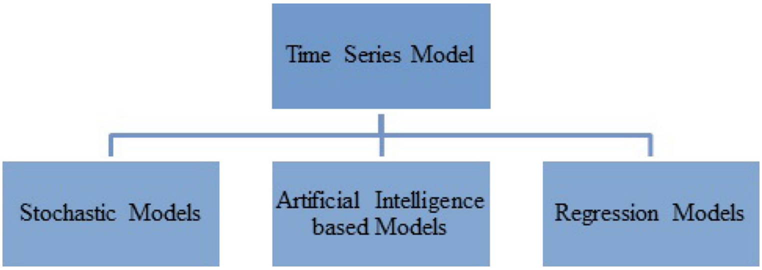

Fig. 1 Classification of time series oil price-forecasting models

The summary of time series forecasting models based on type of model being employed and methods used by researchers have been presented in Table 1. Stochastic models are inspired by financial literature and are widely applied in forecasting of oil prices. There are several stochastic models which have been employed for modelling and forecasting of crude oil prices such as Random Walk [6,7,9,21,22], Mean Reverting Processes [23], Brownian Motion Processes [24], Ornstein–Uhlenbeck Processes [24], Inverse Gaussian Process [19] and Jump Diffusion Processes [25].

Regression type models are based on the relationship between oil price and number of exogenous variables that are known or can be estimated. The most common approaches employing regression models are ARIMA models [12,26,27] and GARCH-family models [6,8,26,28–30]. Arouri et al. [5] employs GARCH models to forecast conditional volatility of spot and future oil prices with structural breaks for better forecasting performance. Huang et al. [31] and Hou [28] presented superior performance of non-parametric GARCH models relative to parametric GARCH models (in-sample and out-of-sample volatility forecasts). Researchers concluded that non-linear dynamical approach is more appropriate for characterizing and predicting crude oil prices than linear approach [32,33]. The parameters of forecasting models for crude oil prices have been estimated by either Least Square Method [12,23,34–38], Full Information Likelihood Method [16], Kalman Filter [23,24] or under Bayesian Framework [39]. However, these numerous estimation algorithms have failed to achieve high prediction accuracy. Stochastic models involving certain characteristics of oil prices and regression models have been kept outside the scope of this review.

A review of these econometric time series models for oil price forecasting has been presented by Frey et al. [40].

Table 1 provide summary of time series models for crude oil price forecasting. In recent times, artificial intelligent models are extensively being used to capture unknown or too complex structure in the time series. Researchers have used artificial intelligent model based approach for oil price forecasting in more than 50 % of the studies listed in Table 1. Out of thirty six studies listed in Table 1, twenty eight studies have considered WTI crude oil spot prices as dependent variable in their studies. Section 3 covers various artificial intelligent models ranging from single models (e.g. neural networks, support vector regression, wavelets) to more complex hybrid versions.

Table 1 Summary of time series models for crude oil price forecasting

References	Oil market	Model type	Methods
[9]	WTI	SM, RM	RW, VaR, ECM
[19]	WTI	SM	IGP
[81]	WTI	RM	ARIMA
[23]	WTI	RM, SM	OLS , MRP
[77]	Br	AI	WNN
[24]	FP	SM	GB, OU
[84]	WTI, Br	RM	GARCH
[26]	FP	RM, AI	ARIMA, GARCH, ANN
[85]	FP	AI	GSM
[10]	WTI	AI	FM
[59]	WTI, Br	AI	SVM
[67]	WTI	AI	SVM
[80]	WTI, Br	AI	ANN
[74]	WTI	AI	WNN
[7]	WTI, Br	AI, RM, SM	WDE, RW, ARMA
[76]	WTI	AI	ANN, WDE
[5]	WTI, FP	RM	GARCH
[86]	FP	RM	RS-EGARCH
[73]	WTI, Br	AI	GA + ANN
[79]	WTI	AI	FNN
[87]	WTI	AI	RMS
[28]	WTI	RM	GARCH
[88]	FP	RM	GARCH
[89]	WTI	AI	WDE
[30]	WTI, Br	RM	GARCH
[56]	WTI	RM	RS-GARCH
[22]	WTI	SM, RM	VECM, NRW, ARIMA
[90]	WTI	RM	CA-VaR
[69]	FP	AI	GA + ANN
[61]	WTI	AI	SVR
[63]	WTI	AI	SVR
[75]	WTI, Br, Du	AI	WNN
[78]	WTI, Br	AI	FNN
[29]	WTI, Br, Du	RM	CGARCH, FIGARCH, IGARCH
[6]	WTI	SM, RM	RW, HM, ARIMA, GARCH, EGARCH, TGARCH, PARCH, CGARCH
[8]	SP	RM	GARCH, EGARCH,APARCH, FIGARCH

2.2 Fundamental models

Fundamental models predict oil prices based on their relationship with economic, financial, social and political indicators that drive them. This study assumes financial and structural models as part of fundamental models. Crude oil prices have been influenced by large number of factors which are complex, noisy, and uncertain [20]. There is no single indicator which can provide a comprehensive portrait of how prices can be determined. Each indicator can give us a snapshot of present condition and modelling of these significant snapshots together provides a clear picture of direction of oil prices. Similar to time series models, fundamental models can also be classified into two major classes: Regression models and artificial intelligent based models as shown in Table 2. This table enlists the analytical methods used by authors for forecasting crude oil prices.

Globalization hypothesis holds that oil prices (WTI-Brent, WTI-Dubai, WTI-Maya and Dubai-Maya) move together and exhibit greater conditional dependency [41]; therefore, most of the study listed in Table 2 considers WTI spot crude oil prices as benchmark price. It is evident from Table 2 that around 50 % of the studies have incorporated artificial intelligent models for forecasting oil prices. As evident from Table 2, researchers have preferred ordinary least square methods for parameter estimation in a regression model. The different input variables, along with the class they belong to, used by different researchers are presented in the next section.

2.2.1 Factors driving oil prices

Oil prices had shown upward trend in 1996 but prices declined drastically by end of 1998. As a consequence of cuts in OPEC production targets, oil prices increased again in late 2000. The impact of such extreme events is of prime importance as they effect the direction of oil prices and thereby the objective of increasing the predication accuracy of crude oil prices. It is important to identify the key indicators driving crude oil prices (during the time-frame of happening of such extreme events) for designing better structural forecasting models. In 2001, 9/11 attack led to increase in volatility of oil prices that soared oil prices till 2004. Oil prices have been steadily rising for several years and in July 2008 stood at a record high of $145/bbl due to low spare capacity. Later, it declined due to global economic crisis at the end of 2008 and then recovered to around $75/bbl by 2010. In 2013, oil prices have set record by surpassing $100/bbl for the first time in that year (in money-of-the-day terms). According to EIA [42], oil prices were rising sharply because global demand (especially in China) was surging and production wasn't adequate to keep up. This led to a boom in unconventional oil production by major energy companies across globe and world's oil supply kept growing by mid-2014. On the other side, due to slowdown in Asia and Europe, the oil demand began weakening. This combination of steadily rising supply and weaker-than-expected demand together with OPEC in favour of letting prices continue to fall pushed oil prices to drop around $55/bbl by end of 2014. This rise or decline in oil prices stimulates for studying in detail the factors behind movements in oil prices. There are large number of factors, which are complex, noisy, and uncertain influencing crude oil prices [20]. Understanding complex oil price movements and indicators driving them

Table 2 Summary of fundamental models for crude oil price forecasting

References	Oil market	Model type	Methods
[57]	WTI	AI	ANN
[43]	WTI	AI	WNN
[35]	WTI	RM	OLS
[36]	WTI	RM	OLS
[37]	WTI	RM	OLS
[38]	WTI	RM	OLS, ECM
[46]	WTI	RM	OLS
[17]	WTI	AI	WNN
[34]	WTI	RM	OLS
[16]	WTI	RM	OLS, FIML, ECM
[12]	WTI	RM	OLS, ARMA
[66]	Br	AI	GRNN
[18]	WTI	AI	ANN, TM
[64]	WTI	AI	FNN
[14]	PGRP	AI	ANN
[50]	WTI	RM	VECM
[51]	WTI	RM	ACIX
[55]	WTI	AI	WDE
[52]	FP	AI	WDE
[53]	FP	RM	GARCH
[91]	FP	RM	GARCH
[33]	Br, WTI, Du	RM	ESTAR
[92]	WTI	RM	CGARCH
[39]	WTI	RM	BVaR
[93]	FP	RM	ECM
[65]	SP	AI	ANN
[60]	WTI	AI	SVR
[62]	NF	AI	SVR
[68]	SP	AI	GA
[74]	WTI; Br	AI	WNN
[72]	WTI	AI	WNN

was the impetus for Energy Information Administration (EIA) to launch a monthly report to assess the financial, trading and physical market factors that influence oil prices.

Beside geopolitical and economic events, any fluctuation in demand or supply side also creates imbalance in the market that critically impact oil market participants and makes markets unpredictable. The demand-supply framework plays a crucial role to an extent that it determines the directions of crude oil prices but has not been sole indicator that drives oil prices. Researchers have considered enormous factors such as GDP, inventories, emerging economies and stock market fluctuations to study their influence on oil prices (Table 3 covers this in detail). There is no solitary indicator

Table 3 Summary of factors influencing oil prices

Class	Input variable	Key
Supply	OPEC production	V1
	Non-OPEC production	V2
	World production	V3
	Oil supply	V4
Demand	OECD consumption	V5
	China consumption	V6
	India consumption	V7
	Seasonal demand	V8
	Global demand	V9
	Non-OECD consumption	V10
Inventories	U.S. refinery capacity	V11
	OPEC total liquid capacity	V12
	U.S. gasoline ending stocks	V13
	OECD stocks	V14
	U.S. ending stocks	V15
	U.S. petroleum imports from OPEC	V16
	U.S. petroleum imports from non-OPEC	V17
	U.S. crude oil imports from OPEC	V18
	U.S. crude oil import from non-OPEC	V19
	OECD industrial inventory level	V20
	Crude oil distillation capacity	V21
Price	Historical prices	V22
	Heating oil spot price	V23
	Gasoline oil spot price	V24
	Natural gas spot price	V25
	Propane spot price	V26
	NYMEX crude oil futures	V27
	NYMEX heating oil futures	V28
Reserves	OPEC reserves	V29
	OECD reserves	V30
	No. of well drilled	V31
Economy	GDP growth rate	V32
	U.S. dollar nominal effective exchange rate	V33
	Foreign exchange of GBP/USD	V34
	Foreign exchange of YEN/USD	V35
	Foreign exchange of Euro/USD	V36
	U.S. inflation rate	V37
	U.S. consumer price index	V38
	Population of developed countries	V39
	Population of less developed countries	V40
	S&P500	V41

Table 3 continued

Class	Input variable	Key
	Gold prices	V42
	Producer price index	V43
World events	World event impact factor	V44
	OPEC quota tighten (April 99)	V45
	Sept 11, 2001 attack	V46
Properties	API density	V47
	Sulphur content	V48
	Country	V49
	Time	V50
	No. of weeks	V51

(lags, future prices or macroeconomic variables) that can provide a complete picture on how prices have been determined, however there are few key indicators that have governed and ruled crude oil prices. The key indicators can give us snapshots of fluctuations in oil prices and modelling of these significant snapshots only (as input variables) can give a clear picture on directions of oil prices. The fluctuations in these factors cause complex, volatile, non-linear and chaotic tendency of crude oil prices, therefore, it is important to find the key strategic indicators that are ruling crude oil prices from decades. Thus, it has become crucial to develop predictive models using various influential factors that drive crude oil prices to understand the complex and dynamic nature of oil prices.

This review has identified petroleum inventory level as a virtuous market indicator of change in crude oil price. Inventory levels have been a measure of balance or imbalance between production and demand [43]. Ye et al. proposed a linear forecasting model using relative inventory level as input for oil prices [36] but later improved Linear-RIL model to non-linear-RIL model due to dynamic relationship between them [37]. Pang et al. [43] proposed to consider both crude oil inventory level and petroleum product inventory level as input factors for better forecasting performance. Weiqi et al. [15] constructed a structural econometric model using relative inventory and OPEC production as explanatory variables for short-run oil price forecasts. Other than inventories level, variables like production, net imports and forward prices were taken as independent variables to estimate spot prices by Considine and Heo [44]. The evidence for the non-linear relationship between GDP growth and oil prices has been examined by Hamilton [34] and Kim [45].

Zamani [38] examined a short term quarterly econometric forecasting model using OECD stocks, Non-OECD demand and OPEC supply to forecast WTI crude oil prices. Ye et al. [35] considered the possible substitution for large proportion of world demand and inventory (in form of OECD demand) as input variable compared to U.S demand alone. Dées et al. [46] assessed a structural econometric model to show the immediate impact of OPEC quota decisions and capacity utilization on oil prices. According to BP [1], emerging economies (especially Asia) accounted for major net growth in energy consumption whereas OECD demand remains falling for a third time in last 4 years. Ratti and Vespignani [47] has highlighted that intense increase in China and India liquidity led to increase in real oil price and production. Li and Lin [48] has provided evidence indicating demand from China and India as leading driver in the world oil pricing system since 2003. Zhang and Wang [49] indicated a greater contribution (95.71 %) of crude oil future markets in price discovery function of spot price. Alvarez-Ramirez et al. [13] used fourier analysis to examine the strong relationship between U.S macro economy and crude oil prices. Dées et al. [16] has examined the dynamic relationship between oil prices and OPEC capacity utilization. Murat and Tokat [50] examined the forecasting power of crack spread futures under vector error correction framework to predict spot oil markets. Yang et al. [51] studied the influence of European debt crisis and financial crisis on crude oil prices with the proposed Autoregressive Conditional Interval Model with Exogenous Explanatory Interval Variable (ACIX). He et al. [52] used error correction models to examine the influence of Kilian economic index (as global activity indicator) on crude oil prices.

Bu [53] examined the relationship between speculative traders' position and crude oil future prices using estimates of GARCH model. Basher and Haug [54] proposed a structural vector autocorrelation model to investigate the dynamic relationship between emerging markets, stock prices and oil prices. Chai et al. [39] developed a oil price VaR model based on path-analysis using core influential factors. Zhang et al. [55] proposed an empirical mode decomposition-based event analysis method to estimate the impact of extreme events on crude oil prices. Fong and See [56] suggested regime switching models framework to study factors driving crude oil prices volatility. Ignoring the clear evidence of presence of non-linearity or structural breaks in the oil price series can lead to false imprint on predictability and persistence. Oil prices are shown more sensitive to any change in oil supply by Chai et al. [39] but weekly dependent on exchange rates by Reboredo [41]. The study of factors driving oil prices that are considered in various stochastic or regression models of oil prices forecast is a major area of research and has been kept outside the scope of this review.

Despite above mentioned attempts, oil price prediction has remained a difficult problem due to its complex non-linear and time-varying nature. In addition, recent studies lay emphasis on developing structural econometric models for forecasting crude oil prices without focusing on finding the key drivers of oil prices. Most recently, a category of artificial intelligent models have emerged and are being attempted to predict oil prices. AI based framework for oil price prediction are discussed in detail in Sect. 3. The factors influencing oil prices may be classified within the categories: C1—supply, C2—demand, C3—inventories, C4—price, C5—reserves, C6—economy, C7—world events, and C8—properties.

There are as many as fifty one variables used in different AI related studies for crude oil price forecasting. A detailed list of factors driving oil prices considered in artificial intelligent models, along with the class to which they belong are presented in Table 3. In order to build an effective model, careful attention should be paid on selecting informative and influential inputs which cause changes in prices [57]. However, until recently, the input variables of oil price forecast have been selected on judgemental criteria or trial and error procedures [58–63]. This review discovers that most of the studies were concentrated on non-linearity, non-stationary and time varying properties of oil prices but seldom focused on feature selection method for selecting significant inputs to improve forecasting accuracy. The study identifies that historical oil prices (either daily, weekly or yearly) are the most popular input variables used by researchers. Abdullah [18] has used 22 input variables from the categories as mentioned in Table 3 to achieve high prediction accuracy but the variables were selected on judgemental criteria. To handle optimal long-term oil price forecasting, Azadeh et al. [64] developed a flexible algorithm based on artificial neural networks and fuzzy regression by using oil supply, crude oil distillation capacity, oil consumption of Non-OECD, USA refinery capacity and surplus capacity as economic indicators. The study concluded ANN models outperform FR models in terms of mean absolute percentage error (MAPE). Section 3 discusses in detail the characteristics of different types of artificial intelligent models that used factors listed in Table 3 as input variables for oil price forecasting.

3 Review of methodology

In this section, the studies are segregated on the basis of type of models, starting from single models (such as neural networks, support vector regression, wavelets, genetically evolved models) to more complex and hybrid models. Recently, hybrid models are been extensively used for building oil price forecasting models as they overcome the limitations of single models and provide better forecasting accuracy.

3.1 Neural network based models

In the past , neural networks were being used extensively for oil price forecasting. Neural Networks can model richer dynamics and can approximate any continuous function of inputs [57]. In this category, seven researchers have forecasted oil prices using artificial neural networks as single model. There are many research studies that suggest integration of neural networks with other traditional methods (such as support vector regression, genetic algorithm, or wavelets) by mean of hybrid approach for improving the prediction performance. These studies are discussed in detail in Sect. 3.5. In Table 4, information regarding the data, time scale, input variables for the study, method of input variable selection and preprocessing techniques employed are discussed. Researcher have utilized neural networks for all major oil markets. It is evident from the Table 4 that neural networks can handle large number of input variables.

Abdullah and Zeng [18] integrated 22 quantitative input variables (sub-factors of demand, supply, economy, inventory and population) together with the qualitative data (collected from experts' view and news) using neural networks to predict oil prices for long and short term time period. The authors have utilized manual feature extraction method for finding significant input variables for the study. Most of the studies have pre-processed the raw price data either by scaling range, normalization or cluster classification as shown in Table 4.

This review identified that most of studies have selected input variables based on judgemental criteria or trail and error basis. In Table 5, forecasting performance of various neural networks models has been compared.

Table 4 Data characteristics, preprocessing technique, input variables and its selection method

References	Oil market	Time scale	Input variable	Variable selection	Preprocessing technique
[57]	WTI	D	V22, V27	JC	RMA, NORM
[26]	NF	D	V22	JC	–
[66]	Br	M	V11, V32, V33, V12, V1, V13	TE	CrI is formed
[14]	PGRP	M	V47, V48, V49, V50	SA	SR
[58]	SP	–	V22	JC	SR
[18]	WTI	M	V1, V2, V5, V6, V7, V14, V15, V16, V17, V18, V19, V29, V30, V31, V34, V35, V36, V32, V37, V38, V39, V40	MFA	LD
[65]	SP	D	V22, V23, V24, V25, V26	CA	CC

Table 5 Forecasting performance comparison of neural network models

References	Training data (%)	Testing data (%)	Forecast horizon	Comparison with other models	Level of accuracy
[57]	90	10	3 DA	–	RMSE: 0.53–0.78 ; HR: 53–79
[26]	86	14	1 TPA	ARIMA, GARCH	MSE: 8.14; RMSE: 2.85; MAE: 2.04
[66]	86	14	1 MA	WCI - GRNN	MSE: −1.48–9.84
[14]	70	30	–	–	MSE: 7.24–8.82
[58]	–	–	5 DA	–	NMSE: −0.35; DS: 61; SNR: 25.37; AR: 92
[18]	80	20	–	TEI@I, EMD-FNN-ALNN	RMSE: 2.26;; NMSE: 0.009; DS: 94
[65]	80	20	1 MA	RM	MSE: −2.15–4.73

Neural networks showed superior results compared to benchmark TEI@I methodology and ARIMA-GARCH models as shown in Table 5. The models are validated using Root Mean Square Error (RMSE), Hit Rate (HR), Mean Square Error (MSE), Mean Absolute Error (MAE), Normalized Mean Square Error (NMSE), Annualized Return (AR) and Directional Statistics (DS). Malliaris and Malliaris [65] studied five inter-related energy products for forecasting one-month ahead prices using neural networks. The results thus obtained through neural network consistently led to a MSE less than half than that of the regression predictions. Malliaris and Malliaris [65] used correlation analysis to find significant input variables for their study. The model architecture of seven studies considered under this category is shown in Table 6. Mahdi et al. [58] examined three different neural network models: Multi-layered Perceptron (MLP), Functional Link Neural Network (FLNN) and Self-Organized MLP (SoMLP) for the oil price series. Mahdi et al. [58] compared the prediction capability of SoMLP

Table 6 Neural Networks model's architecture

References	NN type	Learning algorithm	Hidden neurons	Activation function
[57]	MLP, RNN	LM	1–10	Sig
[26]	MLP	GD	5	HTS, Id
[66]	GRNN	–	TE	–
[14]	MLP	BP	15	LSig
[58]	MLP, FLNN, SoMLP	BP, IA	–	–
[18]	MLP	BP	TE	Sig
[65]	–	–	20	–

with MLP and FLNN for ten different data sets including oil prices. The experimental results thus demonstrated that all neural networks performed better by using stationary data and failed to generate profits while using non-stationary data.

Haider et al. [57] presented a short term forecasting model to understand oil price dynamics based on multi-layer feed forward neural network. Several transformation methods were tested with original data and results showed that relative change of simple moving average is the best method amongst other methods. Moshiri and Foroutan [26] examined chaos in daily crude oil future prices using BDS and Lyapunov test. The results indicated that future prices follow complex non-linear dynamic process and showed superiority of ANN model as compared to ARIMA and GARCH models. Movagharnejad et al. [14] designed a neural network to predict the prices of seven different crude oils in Persian Gulf region, provided that the benchmark light oil of Saudi Arabia is known or predicted by another hybrid forecasting method.

Further, this review identifies that number of hidden neuron varies across studies. Haider et al. [57] has fixed the number of neurons in hidden layer ranging from 1–10 while few authors [14,26,65] have fixed a constant value based on judgemental criteria for number of neurons in hidden layer. There is no rule of thumb applied by researchers for finding the optimal number of neuron to be set for hidden layer. Alizadeh and Mafinezhad [66] proposed a general regression neural network forecasting model for Brent crude oil price with particular attention on finding number of features as input data to achieve best performance.

Most of the studies have used sigmoid function as preferable activation function as shown in Table 6. It is evident from the Table 6 that the multi-layered perceptron neural network with back propagation as the learning algorithm is the most popular among researchers for price forecasting.

3.2 Support vector regression models

Oil prices are complex series with mixture of linear and non-linear characteristics underlying data generating processes of different nature. He et al. [63] introduced morphological component analysis to explore the complex nature underlying oil prices. There are few authors who have tested for non-linearity [61,63,67] and normality

Table 7 Data characteristics, preprocessing technique, input variables and its selection method

References	Oil market	Time scale	Input variable	Input selection	Preprocessing
[59]	WTI; Br	W	V22	JC	SR
[60]	WTI	W	V22, V27, V8, V51, V44, V9	JC	SR
[61]	WTI	D	V22	JC	RT
[62]	NF	D	V22, V33, V28, V41	JC	CC
[63]	WTI	D	V22	JC	WT; RT
[67]	WTI	M	V22	JC	RT

assumptions [61,63] of oil price series. Support vector regression has an advantage of reducing the problem of over-fitting or local minima. Khashman [60] experimental results proved SVM could be used with a high degree of precision in predicting oil prices. Bao et al. [59] presented a comparative study of recursive and direct strategies of multi-step ahead prediction for both WTI and Brent crude oil spot prices with support vector regression. As compared to results obtained through benchmark ARMA and Random Walk models for crude oil price prediction, He et al. [61] confirmed the superiority of the proposed slantlet denoising algorithm based on SVR model. Zhu [62] formulated a two-stage structure for modelling oil future prices by partitioning the whole input data space into mutually exclusive regions by K-mean clustering algorithm and then corresponding SVM models. Table 7 showed that each study have preprocessed raw price data either by scaling range, return transformation or by cluster classifier.

Most of the authors have used WTI as benchmark oil price data in their studies. An important research gap in selection of input variables through judgemental criteria or by literature review is highlighted under this category. It is evident from Table 8 that most of the authors have compared SVM with linear models. Xie et al. [67] has shown SVM model performed better than back-propagation neural networks. The model proposed by Zhu [62] has shown better performance in terms of MSE, MAE and MAPE compared to standard SVM model. Radial basis kernel function is the most popular choice among researchers for a price forecast problem as seen from Table 9. The values for epsilon, cost and gamma vary across different studies. He et al. used gradient search method to set appropriate model parameters [61,63]. Xie et al. [67] and He et al. [63] have used directional statistics as performance criterion to compare their respective models with traditional stochastic or regression models.

3.3 Genetically evolved models

Kaboudan [68] performed short term monthly forecasting of crude oil price using genetic programming (GP) and neural networks. The study presented that GP can produce impressive one-month ahead forecast compared to that by Random Walk and ANN. This GP based oil price forecasting framework by Kaboudan [68] is considered as benchmark for comparison by Amin-Naseri [69].

Table 8 Forecasting performance comparison of support vector regression models

References	Training data (%)	Testing data (%)	Forecast horizon	Comparison with other models	Level of accuracy
[59]	71	29	4, 8, 12 WA	DirS, RecS	RMSE: 5.05–52.11; MAPE: 10.23
[60]	50	50	1 WA	–	PR: 81.27 %
[61]	60	40	–	ARMA, RW	MSE: 4.65
[62]	95	5	–	S-SVM	MSE: 1.37; MAE: 0.95; MAPE: 1.15
[63]	60	40	–	RW, ARMA	MSE: 8.74; DS: 53.07 %
[67]	88	12	1 MA	ARIMA, BPNN	RMSE: 2.19; DS: 70.83 %

Table 9 Support vector regression model architecture

References	Kernel function	Epsilon	Cost	Gamma	Model parameters
[59]	RB	0.01	–	–	–
[60]	RB	–	2965820	0.001953	2^{-15} to 2^{15}
[61]	RB	6.64×10^{-16}	24.25	27.86	GSM
[62]	RB	–	–	–	[0,1]
[63]	RB	7.81×10^{-3}	$0.5 - 8$	3.90×10^{-3}	GSM
[67]	RB	–	–	–	–

Table 10 Data characteristics, preprocessing technique, input variables & its selection method

References	Oil market	Time scale	Input variable	Input selection	Preprocessing
[68]	SP	M	V22, V3, V5, V15	TE	–
[70]	WTI; Br	D	–	TE	–

Xiao et al. [70] combined transfer learning techniques with analog complexing and genetic algorithm for crude oil price forecasting. However, there is no information as to how the input variables are selected in studies mentioned in Table 10. According to Table 11, Xiao et al. [70] showed that genetically evolved models performed better in comparison to neural networks and ARIMA family models based on MSE,

RMSE and directional statistics. There is lack of information with respect to preprocessing technique and fitness function used by authors as shown in Table 12. The new combined models based on genetic algorithm with neural networks and that with SVM are discussed in Sect. 3.5.

Table 11 Forecasting performance comparison of genetically evolved models

References	Forecast horizon	Comparison with other models	Level of accuracy
[68]	1–12 MA	ANN; RW	MSE: 0.24–1.85;
[70]	1 TPA	ARIMA; ANN; GPMGA; AC	RMSE: 1.0691; DS: 79.02

Table 12 Genetically evolved model's architecture

References	Cross-over probability	Mutation probability	Fitness function
[68]	0.02	0.06	–
[70]	0.9	0.05	–

3.4 Wavelet-based models

A wavelet-based prediction model is proposed to provide forecast over 1–4 months' horizon and to compare with future oil price data by Yousuf [71]. He et al. [7] introduced the wavelet decomposed ensemble model to analyse dynamic changing nature of underlying oil market structure. This study found that hybrid version comprising of wavelet with neural networks is more appealing to researchers as compared to single wavelet based model.

3.5 Hybrid models

3.5.1 Genetic Algorithm and Neural Network

Amin-Naseri [69] proposed a hybrid artificial intelligence model combining local approximation techniques with genetically evolved neural network. The author used Hannan-Quinn info criterion (HQIC) as fitness function and set number of hidden neurons in range from 1–30. The performance of the model was evaluated with three competing frameworks (STEO, KAB and WANG) for oil price forecasting. The proposed model has performed well in terms on MSE, RMSE and directional statistics, and has found to be effectively mapping the non-linearity and non-normality present in crude oil price data. The proposed model has been considered as benchmark model for comparison by Alexandridis and Livanis [72]. Fan et al. [73] presented Generalized Pattern Matching based on Genetic Algorithm (GPMGA) to predict future prices. GPMGA overcomes some limitations of Elman Networks and Pattern Modelling in Recognition System (PRMS) approach for multi-step prediction of oil prices.

As evident from Table 13, authors have preprocessed raw price data to achieve high level of accuracy. Authors have preferred autocorrelation function and partial autocorrelation function to determine the optimal number of lags for model identification and estimation.

The review states that genetically evolved neural networks are superior to other competitive models as mentioned in Table 14. The studies under this category have utilize sigmoid function as activation function. The number of neurons in hidden layers varies as seen from Table 15.

Table 13 Data characteristics, preprocessing technique, input variables & its selection method

References	Oil market	Time scale	Input variable	Input selection	Preprocessing
[69]	FP	M	V22	PACF	CC
[73]	WTI; Br	D	V22	GT; ACF	Standardization

Table 14 Forecasting performance comparison of Genetic Algorithm and Neural Network models

References	Training data (%)	Testing data (%)	Forecast horizon	Comparison with other models	Level of accuracy
[69]	95	5	–	STEO; KAB; WANG	MSE: 0.90–9.10; RMSE: 0.95–3.02; DS: 71–81 %
[73]	99	1	1 MA	PRMS; ENN	RMSE: 1.57–2.43

Table 15 Genetic Algorithm and Neural Networks model's architecture

References	Model type	Learning Algorithm	Hidden neurons	Activation function	Fitness function	Cross-over probability	Mutation probability
[69]	MLP	LM; GD	1–30	LSig	HQIC	0.9	0.01
[73]	RNN	BP	TE	TSig	–	0.9	0.09

3.5.2 Wavelet and Neural Network

Mingming et al. [74] proposed a multiple wavelet recurrent neural network based hybrid method for international crude oil prices. This model utilized wavelet analysis to capture multi scale data characteristics, while designing an appropriate recurrent neural network to predict oil prices at different time scales, followed by a standard back-propagation neural network to combine these independent forecasts. He et al. [75] proposed an ensemble approach incorporating wavelet and feed-forward neural network for estimating VaR in crude oil market to further improve modelling accuracy and reliability of three oil markets: WTI, Brent and Dubai. Jinliang et al. [17] decomposed crude oil price time series into several trend and random component. For higher prediction accuracy, the trend component of oil prices is predicted with Boltzmann neural network and the random component is predicted with Gaussian kernel density function as shown in Table 16. Jammazi and Aloui [76] examined a short term forecasting of monthly WTI prices with different input-hidden nodes combinations and three types of activation functions. The results highlighted combination of Harr A Trous wavelet function with back propagation neural network as a promising forecasting tool. Pang et al. [43] proposed to predict monthly oil prices using OECD inventory level as independent variable, and used wavelet theory based feed forward neural network to model the non-linear relationship between oil prices and inventory.

Table 16 Wavelet and Neural networks model's architecture

References	Model type	Learning algorithm	Hidden neuron	Activation function
[74]	RNN; MLP	BP	TE	LSig
[75]	MLP	LM	6	LSig
[17]	BNN	–	–	–
[76]	MLP	BP	TE	BiP Sig
[43]	MLP	GD	8	–
[77]	RBF	–	4	–
[72]	WNN	–	1	–

Table 17 Data characteristics, preprocessing technique, input variables and its selection method

References	Oil market	Time scale	Input variable	Input selection	Preprocessing	Wavelet function
[74]	WTI, Br	A	V22, V42	JC	WT	Db
[75]	WTI, Br, Du	W	V22	JC	RT, WT	HaT; Db; Coiflet
[17]	WTI	M	V22, V42	JC	WT	Db
[76]	WTI	M	V22	JC	WT	HaT
[43]	WTI	M	V22, V20, V45, V46	JC	WT	Morlet
[77]	Br	M	V22	JC	WT, SR	Db
[72]	WTI	M	V22, V43, V3	CA	WT	–

The proposed model achieved lower RMSE, MAPE and MAE in comparison to both linear and non-linear relative inventory models.

Qunli et al. [77] decomposed the original price sequence successfully using discrete wavelet transform as input layer of radial basis function neural network. Alexandridis and Livanis [72] used wavelet neural network to forecast monthly WTI crude oil spot prices using price lags, world crude oil production and the producer price index for petroleum as explanatory variables.

Out of seven articles listed in Tables 17, 18 only one author has emphasized on selecting input variables based on correlation analysis. Correlation analysis is a measure of linear relationship between variables but macroeconomic variables exhibit non-linear relationship with oil prices. Therefore, there is a requirement to develop a method for identifying significant input indicators based on non-linear relationship that exists between variables. It can be observed that Daubechies has been adopted by most researchers as a wavelet function. The prediction accuracy of combined models is evaluated with linear ARMA family, non-linear neural networks, STEO, WANG and AMIN models.

3.5.3 Fuzzy Neural Network

Panella et al. [78] favoured the quality of forecasting accuracy based on neurofuzzy approach (adaptive neuro-fuzzy inference system) in comparison to other linear and

Table 18 Forecasting performance comparison of Wavelet and Neural Network models

References	Training data (%)	Testing data (%)	Forecast horizon	Comparison with other models	Level of accuracy
[74]	70	30	4–8; 8–16; 16–32 YA	–	MSE: 3.88–4.06
[75]	36	24	–	ARMA-GARCH	MSE: 0.0059–0.0131
[17]	–	–	–	–	–
[76]	80	20	19 MA	MLP	MSE: 3.89; HR: 73 %; R^2: 0.997
[43]	82	18	1 MA, 2MA, 3MA	L-RIM, NL-RIM	RMSE:1.486; MAE:1.073; MAPE:2.263
[77]	68	32	–	–	SSE: 6.16×10^{-5}
[72]	56	50	1MA, 3MA, 6MA	WANG, AMIN, STEO	MSE: 2.05; MAE: 1.02; Max AE: 7.36

Table 19 Data characteristics, preprocessing technique, input variables and its selection method

References	Oil market	Time scale	Input variable	Input selection	Preprocessing
[78]	WTI; Br	D	V22	JC	LT; CC
[79]	WTI	D	V22	JC	SMP
[64]	WTI	A	V11, V4, V21, V10	JC	–

neural network models. Ghaffari and Zare [79] presented a method based on soft computing approaches to forecast WTI crude oil spot prices for one-month ahead forecast horizon. Azadeh et al. [64] used oil supply, surplus capacity, Non-OECD consumption, U.S. refinery capacity and crude oil distillation capacity as input variable for designing a flexible ANN-FR algorithm to model noisy and complex oil prices. Further, the ANOVA and Duncan multiple range test are used to test the significance of the forecast obtained from ANN and FR models. Table 19 indicates that the input variables has been selected based on judgemental criterion and no prior selection method has been applied.

Ghaffari [79] explored the possibility of smoothing procedure as preprocessing tool to explore the pattern of oil prices while Panella et al. [78] incorporated both log transformation and cluster classification. As clear from Table 20, the prediction accuracy of proposed neuro-fuzzy model by Panella et al. [78] has been compared with linear and non-linear models on the basis of noise-to-signal ratios.

Ghaffari [79] has compared the results of their respective models with and without smoothing procedure and observed that prediction quality in terms on percentage of correct predictions has been improved by smoothing oil price data. It is evident from Table 21 that researchers preferred to develop fuzzy model by adopting Takagi–Sugeno–Kang as fuzzy inference system and Gaussian as membership function. The

Table 20 Forecasting performance comparison of Fuzzy Neural Network models

References	Training data (%)	Testing data (%)	Forecast horizon	Comparison with other models	Level of accuracy
[78]	67	33	1 SA	LSE; RBF; MoGNN	NSR: −46 to −24
[79]	80	20	30 DA	WSP	PCP: 68.18–70.09
[64]	80	20	–	ANN, FR	MAPE: 0.035

Table 21 Fuzzy Neural Networks model's architecture

References	Model type	Learning Algorithm	Hidden neurons	Fuzzy inference system	Membership function
[78]	MLP	LSE + BP	TE	TSK	Gaussian
[79]	MLP	LSE + GD	TE	TSK	Gaussian
[64]	MLP	BFGS; BR; BLR; GDX; LM	TE	–	Gaussian

multi-layered perceptron neural network is the most popular among researchers for oil price forecasting under this category of neuro-fuzzy approach. Azadeh [64] model architecture includes MLP along with five variant of learning algorithm to improve the forecasting performance and achieved MAPE as low as 0.035.

3.5.4 Decomposition based Neural Network

Yu et al. [80] proposed a "decomposition-and-ensemble" strategy using EMD-based NN ensemble learning model to predict oil prices. Empirical mode decomposition is proposed to decompose oil price data into eleven intrinsic mode functions. Xiong et al. [81] evaluated the performance of EMD-based feed-forward neural network framework incorporating slope-based method for oil price forecasting with three leading strategies: direct, iterative and multiple-input multiple-output (MIMO).

Xiong et al. [81] used Symmetric MAPE (SMAPE) as a forecasting performance criterion to evaluate the performance of EMD based neural network. In Table 22, partial mutual information is used to examine the relationship between historic prices and oil prices together with forward backward selection and delta test for model identification and estimation. Multi-layered perceptron neural network is the most widely used neural network architecture by researchers for hybrid models as evident from Tables 23, 24.

3.5.5 Support vector and Genetic Algorithm

Guo [82] improved traditional SVR forecast precision by using genetic algorithm optimized parameter of SVR in accordance with the training data. The model is found to be effective in mapping the complexities of oil price series. Gabralla [83] investigated

Table 22 Data characteristics, preprocessing technique, input variables and its selection method

References	Oil market	Time scale	Input variable	Input selection	Preprocessing
[80]	WTI; Br	D	V22	JC	–
[81]	WTI	W	V22	PMI; DT; FBS	SR

Table 23 Forecasting performance comparison of decomposition based Neural Network models

References	Training set (%)	Testing set (%)	Forecast horizon	Comparison with other models	Level of accuracy
[80]	72	28	1 DA	ARIMA; MLP	RMSE: 0.273–0.225; DS: 86.99–87.81
[81]	67	33	4 WA	MLP	SMAPE: 2.28–8.15; MAE: 0.81–1.28; DS:54–87

Table 24 Decomposition based Neural Networks model's architecture

References	Model type	Learning Algorithm	Hidden neurons	Activation function	Decomposition method	No. of IMF's
[80]	MLP; ALNN	BP	–	Lgs; Lin	EMD	11
[81]	MLP	LM	15	–	EMD	–

performance of two different algorithms for feature selection together with several machine learning methods (IBL, KStar and SMOreg) for oil price prediction.

4 Limitations

There is no solitary indicator driving crude oil prices. The output is based on how much information is contained in the set of input variables selected for the study. There are many studies that had examined the relationship between oil prices and macroeconomic variables but there seem no consensus on the extent to which these macroeconomic variables drive oil prices. Existing studies of predicting oil prices have accounted for non-linearity, non-stationary and time-varying structure of the oil prices but have seldom focus on selecting significant features with high predicting power. The empirical literature is very far from any consensus about selecting the appropriate features/indicators that explains the characteristics of oil market. In most of the studies, the design of input vector for oil price forecasting model is carried out on judgemental criteria or trial and error procedures. Little attention is paid on selecting influential factors and more on assessing new techniques for oil price forecasting.

The effect of input variables is considered to constantly driving oil prices in different studies. There is shift in the influence of input variables subject to happening of any geopolitical and economic events in a given time-period but there is no literature available that highlights this point. Predicted oil prices are dependent on short term macroeconomic indicators whose effects are subject to structural changes. Few studies have been carried out using artificial intelligent models to forecast complex oil price series as compared to its application in diverse fields. Recently, researchers suggest integration of neural networks with traditional methods as support vector regression, genetic algorithms or wavelets by mean of hybrid approach to overcome limitations of single models.

5 Concluding remark

Off late, artificial intelligent models are being extensively used to capture unknown or too complex structures in time series. This review focussed on artificial intelligent based oil price forecasting models and attempted to provide in-depth review based on the following parameters: (i) type of model, (ii) input variables, (ii) input variable selection method, (iv) data characteristics, (v) forecasting performance, and (vi) model architecture. It enlisted the numerous key indicators used as input variables in artificial intelligent based oil price forecasting models and attempted to highlight a serious issue of selecting input variables based on judgemental or trial and error basis.

This review concludes that there is no single indicators driving oil prices and there is need to identify the relevant input variables for oil price predictions. Multi-layered perceptron neural network is most widely used by researchers for price forecasting. Recently, researchers suggests integration of neural networks with traditional methods as support vector regression, genetic algorithms or wavelets by mean of hybrid approach to overcome limitations of single models. It also highlighted that effect of factors is constraint to happening of geopolitical and economic events. The research gap highlighted to develop a robust feature selection method that can account for non-linearity and time-varying structure of oil prices.

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