Influential Article Review - Predicting the Price of Crude Oil: A Bayesian Approach

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This paper examines innovation 2019. We present insights from a highly influential paper. Here are the highlights from this paper: This paper proposes a hybrid Bayesian Network (BN) method for short-term forecasting of crude oil prices. The method performed is a hybrid, based on both the aspects of classification of influencing factors as well as the regression of the out-of-sample values. For the sake of performance comparison, several other hybrid methods have also been devised using the methods of Markov Chain Monte Carlo (MCMC), Random Forest (RF), Support Vector Machine (SVM), neural networks (NNET) and generalized autoregressive conditional heteroskedasticity (GARCH). The hybrid methodology is primarily reliant upon constructing the crude oil price forecast from the summation of its Intrinsic Mode Functions (IMF) and its residue, extracted by an Empirical Mode Decomposition (EMD) of the original crude price signal. The Volatility Index (VIX) as well as the Implied Oil Volatility Index (OVX) has been considered among the influencing parameters of the crude price forecast. The final set of influencing parameters were selected as the whole set of significant contributors detected by the methods of Bayesian Network, Quantile Regression with Lasso penalty (QRL), Bayesian Lasso (BLasso) and the Bayesian Ridge Regression (BRR). The performance of the proposed hybrid-BN method is reported for the three crude price benchmarks: West Texas Intermediate, Brent Crude and the OPEC Reference Basket. For our overseas readers, we then present the insights from this paper in Spanish, French, Portuguese, and German.

Keywords:Bayesian networks, Random Forest, Markov chain Monte Carlo, Support vector machine

SUMMARY

- The price data of oil/OVX/VIX were acquired through the Quandl package . As for the crude price, the data related to three benchmarks were collected: West Texas Intermediate , Brent crude , and the OPEC Reference Basket .
- A number of seven distinct IMFs and one residue were detected for WTI , while for BRENT/ORB, eight IMFs were detected.
- Descriptive statistics of the IMFs/residue of ORB, in the period between 06-July-2007 and 25-February-2019. The technical indicators were computed using the TTR package . However, it should be noted that because the oil price data used contained the closing price values, the CCI numbers obtained herein essentially receive an altered meaning to their original definition. Table 5 lists the set of significant external regressors, separately detected by the BN-QRL-BLasso-BRR methods, for each IMF/residue of WTI. Figure 2 provides a graphical representation of the extracted Bayesian network of significant/insignificant previous-time

external regressors of the IMFs/residue of WTI, obtained through the constraint-based BN concept.
- The final set of external regressors for each IMF/residue of ORB. The partial autocorrelation of the Intrinsic Mode Functions- IMF.1 , IMF.2 , IMF.3 , IMF.4 , IMF.5 , IMF.6 , IMF.7 - and the residue of WTI
- The hybrid strategy optimization was used within the GARCH implementation in Methods 1–5. This ensures that a number of non-linear solvers are called in a sequence in the case that the initial optimization fails. For the SVM implementation , a grid-search was initially conducted over the parameter ranges so as to calibration the SVM model . This was followed by a kernel-based SVM regression, where the hyperparameters of the kernel were taken as those obtained from the calibration stage. The Laplacian kernel was used within the SVM regression with bound constraint . For the NNET predictions , the k-nearest neighbor method was used without any preprocessing of the predictor data . As for the MCMC , a number of 1,000 burn-in iterations was elapsed, followed by 10,000 Metropolis iterations for the sampler.
- The extracted Bayesian networks indicate that both OVX and VIX are influential on different layers of IMF or the residue, which accounts for their impact on the value of future crude prices.
- Conclusions. The performance of the hybrid Bayesian network proposition was outstanding compared to the other devised hybrid models, in all of the three crude price types and against all of the three statistical benchmarks .

HIGHLY INFLUENTIAL ARTICLE

We used the following article as a basis of our evaluation:

Fazelabdolabadi, B. (2019). A hybrid Bayesian-network proposition for forecasting the crude oil price. Financial Innovation, 5(1), 1–21.

This is the link to the publisher’s website:
https://jfin-swufe.springeropen.com/articles/10.1186/s40854-019-0144-2

INTRODUCTION

The price of crude oil has a pivotal role in the global economy and remains at the core of energy markets. As such, its fluctuations have the potential to impact economic developments worldwide. The ability to forecast the price of crude oil is therefore a useful tool in the management of most industrial sectors (Shin et al. 2013). Nevertheless, crude oil price forecasting has been a challenging task, owing to its complex behavior resulting from the confluent influence of several factors on the crude oil market. In specific, the nonlinear features exhibited in the dynamics of oil price volatilities present a quandary for predictive techniques, making the issue of (long-term) crude price forecasting open to finance research.

A wealth of literature exists on the topic of forecasting crude oil prices. These articles are myriad, both in terms of the types of models and the number of methods being used concurrently. Some studies use an approach with a single method (non-hybrid) and some are defined by several methods (hybrid). In this regard, the generalized autoregressive conditional heteroskedasticity (GARCH) was amongst the first methods used because of its ability to capture time-varying variance or volatility (Agnolucci 2009; Arouri et al. 2012; Cheong 2009; Fan et al. 2008a; Hou and Suardi 2012; Kang et al. 2009; Mohammadi and Su 2010; Narayan and Narayan 2007; Sadorsky 2006; Wei et al. 2010). We attempted to perform the GARCH model as a hybrid method by combining with other models, such as the stochastic volatility (SV) model, the implied volatility (IV) model and the support vector machine (SVM) model.

The neural network (NNET) method has been another approach for crude price forecasting (Azadeh et al. 2012; Ghaffari and Zare 2009; Movagharnejad et al. 2011; Shin et al. 2013; Wang et al. 2012; Yu et al. 2008; Zhang et al. 2008). However, it reportedly bears the disadvantage of over-fitting, local minima and weak generalization capability (Zhang et al. 2015). For this sake, its hybrid usage has been recommended for the purposes of crude price forecasting.

Some authors opted to use the SVM model for price prediction, taking advantage of its suitability for modeling small-sized data samples with nonlinear behavior (Guo et al. 2012). Others have reported on the merits of the wavelet technique for crude price forecasting (Yousefi et al. 2005) with one major shortcoming being its sensitivity to the sample size. However, the recent literature advocates for the use of hybrid methods to improve on the accuracy of price forecasting. The use of the best of each technique in a hybrid framework has been enhanced by combining the soft-computing or econometric method or both (Fan et al. 2008b; Xiong et al. 2013). The reader is referred to the excellent review by Zhang et al. (2015) for a more complete assessment of past research on oil price forecasting.

The motivation behind the present work was to exploit the potential of Bayesian network (BN) theory, in the context of crude price prediction, by constructing a network over decomposed price components. As such, the present article contributes to the existing literature in this field by proposing a novel hybrid method within a Bayesian network framework. In addition, this article reports results on other devised hybrid methods, using Random Forest (RF), Markov Chain Monte Carlo (MCMC), NNET and SVM. The rest of the article is organized as follows. The next section will detail the methods being used. A description of the results is provided in the third section, which will be followed by some concluding remarks.

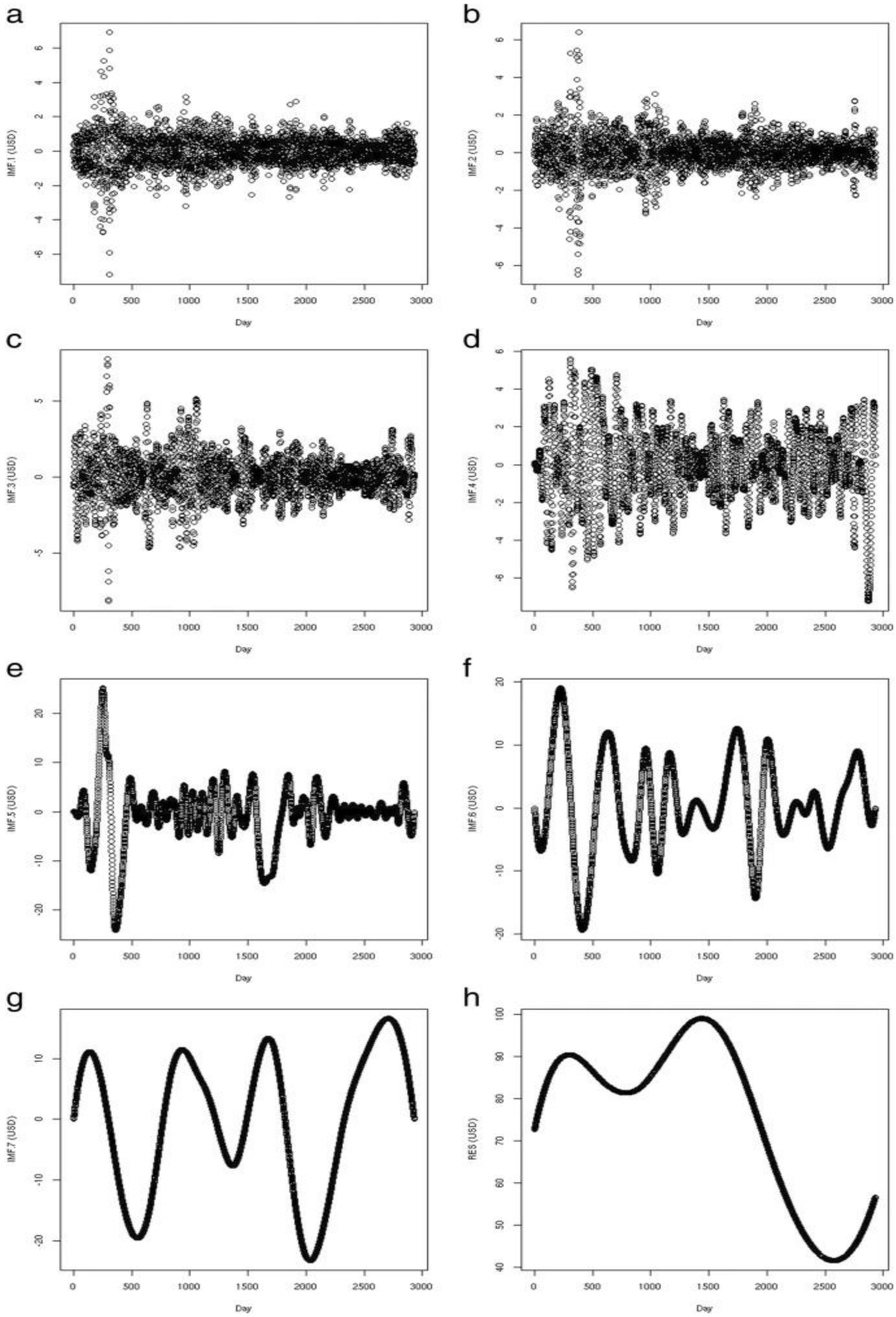
CONCLUSION

The performance of the hybrid Bayesian network proposition was outstanding compared to the other devised hybrid models, in all of the three crude price types (WTI, BRENT and ORB) and against all of the three statistical benchmarks (MAE, RMSE and MAPE). The BN demonstrated that the volatility indices (OVX, VIX) are influential on different decomposed signals of the crude price, affecting the level-ahead price values. The predictive power of the hybrid methods adopting GARCH was shown to be inferior to the other methods, which apply regressions to all of the layers of the decomposed signal for crude price forecasting. Since the proposed hybrid method makes use of regressors with short-term life spans (i.e., technical indicators, OVX, VIX and past price values), the method remains a valid option for short-term forecasting. The question of its capability in handling long-term price forecasts is yet to be answered by the future research using parameters with longer-term viability.

APPENDIX

FIGURE 1

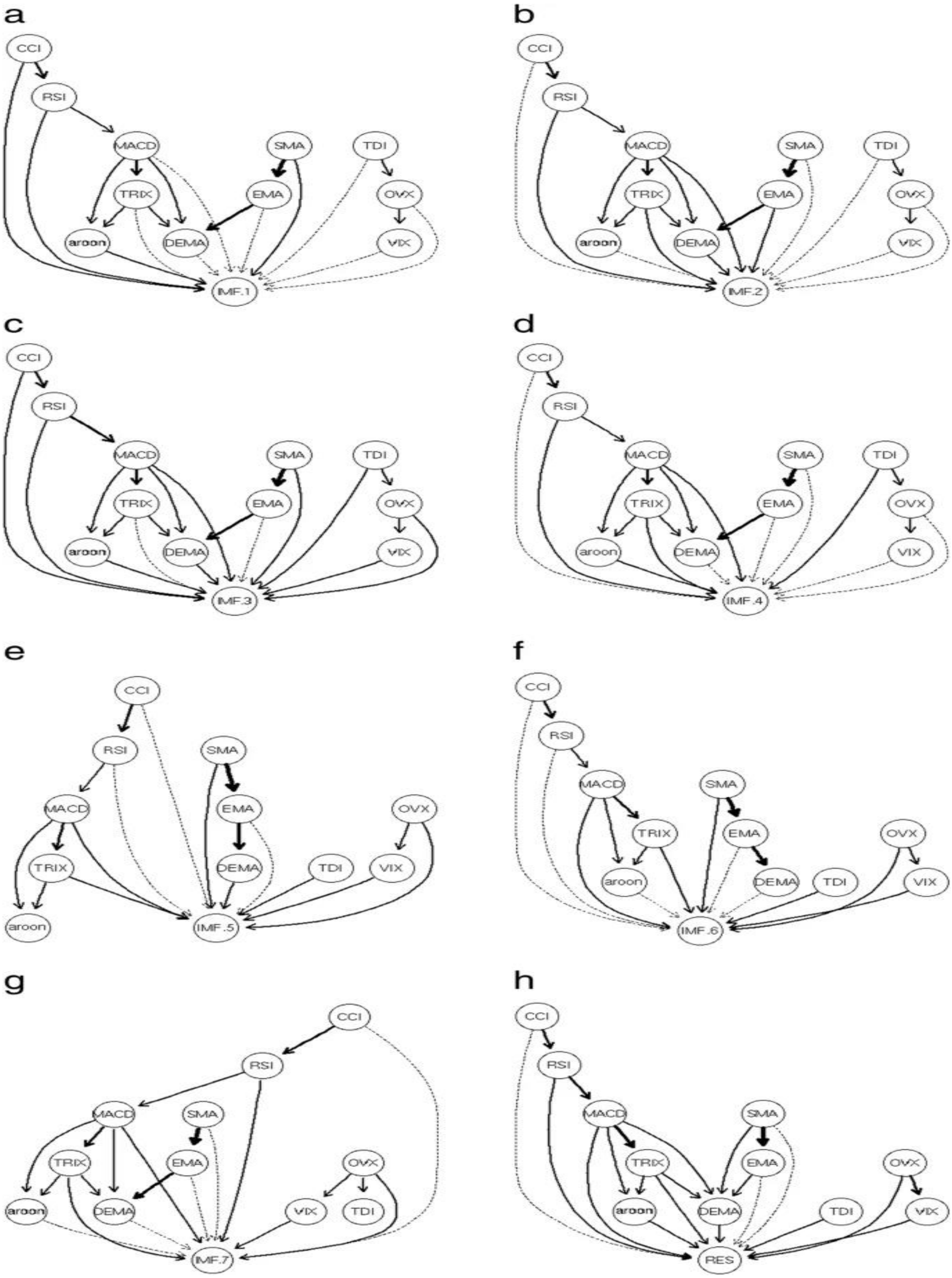
THE INTRINSIC MODE FUNCTIONS



IMF.1 (a), IMF.2 (b), IMF.3 (c), IMF.4 (d), IMF.5 (e), IMF.6 (f), IMF.7 (g) - and the residue (h), decomposed from WTI price data by the EMD method

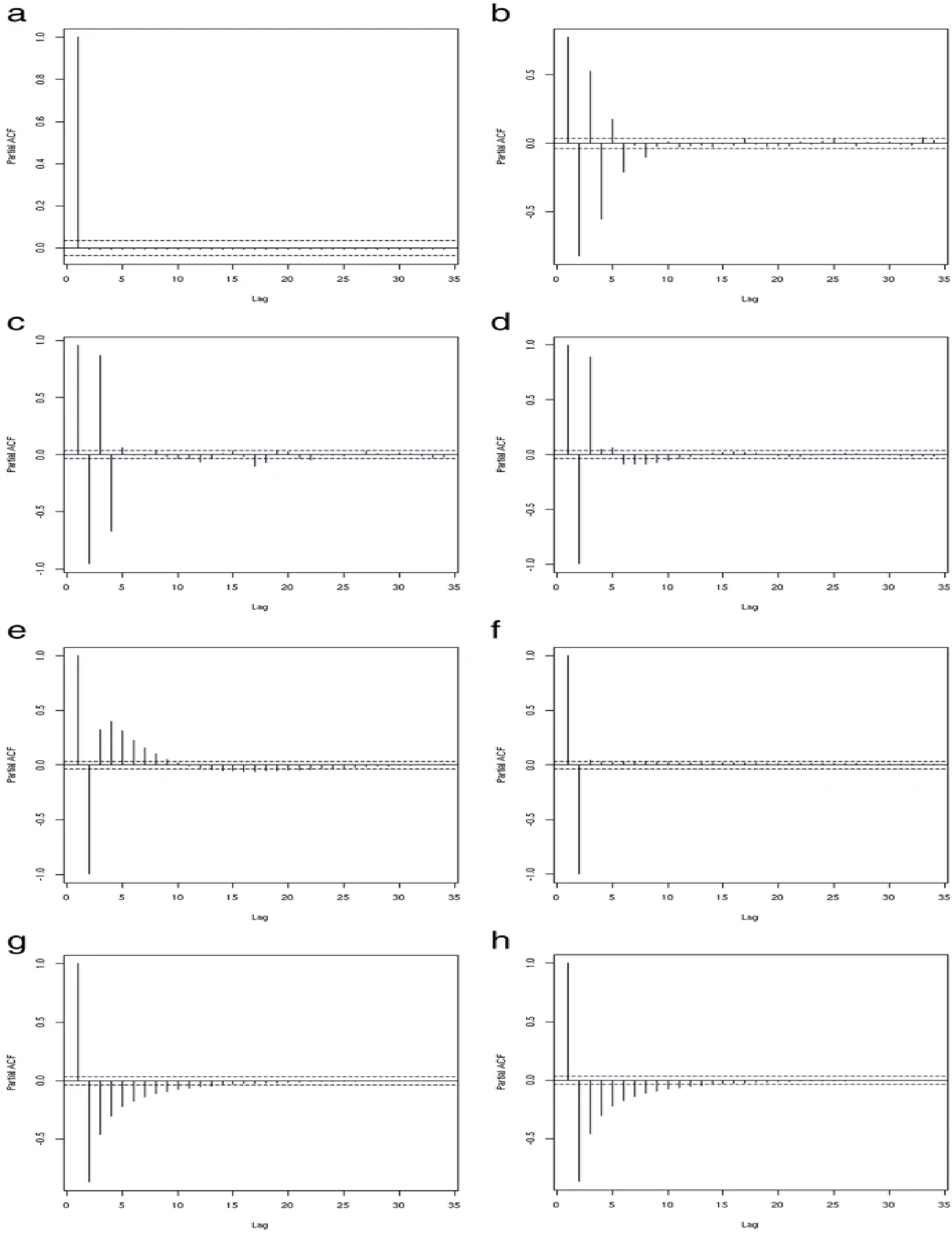
FIGURE 2

THE BAYESIAN NETWORK OF SIGNIFICANT (SOLID LINES), INSIGNIFICANT (DASHED LINES) OF EXTERNAL REGRESSORS FOR THE INTRINSIC MODE FUNCTIONS



IMF.1 (a), IMF.2 (b), IMF.3 (c), IMF.4 (d), IMF.5 (e), IMF.6 (f), IMF.7 (g) - and the residue (h) of WTI, extracted through the constrained-based BN method

FIGURE 3
THE PARTIAL AUTOCORRELATION OF THE INTRINSIC MODE FUNCTIONS



IMF.1 (a), IMF.2 (b), IMF.3 (c), IMF.4 (d), IMF.5 (e), IMF.6 (f), IMF.7 (g) - and the residue (h) of WTI

TABLE 1
DIFFERENT PREDICTIVE STRATEGIES TESTED

Name	Strategy
Method-1	RF + GARCH
Method-2	SVM + GARCH
Method-3	MCMC+GARCH
Method-4	NNET+GARCH
Method-5	BN + GARCH
Method-6	RF
Method-7	SVM
Method-8	MCMC
Method-9	NNET
Method-10	BN

TABLE 2
DESCRIPTIVE STATISTICS OF THE IMFS/RESIDUE OF WTI, IN THE PERIOD BETWEEN 06-JULY-2007 AND 25-FEBRUARY-2019

Name	augmented Dickey–Fuller (ADF)[a]	Kwiatkowski-Phillips-Schmidt-Shin (KPSS) [b]	Jarque–Bera	Kurtosis	mean	Standard Deviation
IMF.1	−15.24 (0.01)	0.22 (0.1)	3781.20 (0.000)	8.567	0.0035	0.92
IMF.2	−16.79 (0.01)	0.03 (0.1)	3917.50 (0.000)	8.66	0.0008	0.97
IMF.3	−13.84 (0.01)	0.022 (0.1)	901.49 (0.000)	5.711	−0.0066	1.567
IMF.4	−8.63 (0.01)	0.062 (0.1)	81.49 (0.184)	3.622	−0.1983	2.266
IMF.5	−7.82 (0.02)	0.180 (0.1)	564.44 (0.000)	5.139	−0.1187	6.445
IMF.6	−3.70 (0.01)	0.276 (0.1)	878.23 (0.000)	5.682	0.2289	7.557
IMF.7	−2.30 (0.45)	1.519 (0.01)	244.24 (0.000)	2.127	−1.2018	10.844
RES	−1.83 (0.64)	20.624 (0.01)	366.29 (0.000)	1.755	76.7498	16.129

[a] Alternative hypothesis: Data is stationary
[b] Null hypothesis: Data is level stationary

TABLE 3
DESCRIPTIVE STATISTICS OF THE IMFS/RESIDUE OF BRENT, IN THE PERIOD BETWEEN 06-JULY-2007 AND 25-FEBRUARY-2019

Name	augmented Dickey–Fuller (ADF)[a]	Kwiatkowski-Phillips-Schmidt-Shin (KPSS) [b]	Jarque–Bera	Kurtosis	mean	Standard Deviation
IMF.1	−14.78 (0.01)	0.204 (0.1)	554.27 (0.000)	5.132	0.0001	0.81
IMF.2	−18.008 (0.01)	0.067 (0.1)	870.12 (0.000)	5.674	0.0263	1.00
IMF.3	−16.059 (0.01)	0.024 (0.1)	1281.5 (0.000)	6.247	−0.0294	1.55
IMF.4	−10.714 (0.01)	0.023 (0.1)	152.74 (0.000)	4.115	0.0302	1.81
IMF.5	−5.140 (0.01)	0.127 (0.1)	511.08 (0.000)	4.914	0.094	5.57
IMF.6	−6.923 (0.01)	0.273 (0.1)	4365.10 (0.000)	8.566	0.0213	7.83
IMF.7	−3.055 (0.13)	2.841 (0.01)	28.49 (0.000)	2.802	0.597	11.88
IMF.8	−2.574 (0.33)	2.841 (0.01)	28.49 (0.000)	2.716	−2.403	7.51
RES	−2.896 (0.19)	14.343 (0.01)	186.48 (0.000)	1.861	82.330	20.49

[a] Alternative hypothesis: Data is stationary
[b] Null hypothesis: Data is level stationary

TABLE 4
DESCRIPTIVE STATISTICS OF THE IMFS/RESIDUE OF ORB, IN THE PERIOD BETWEEN 06-JULY-2007 AND 25-FEBRUARY-2019

Name	augmented Dickey–Fuller (ADF)[a]	Kwiatkowski-Phillips-Schmidt-Shin (KPSS)[b]	Jarque–Bera	Kurtosis	mean	Standard Deviation
IMF.1	−15.60 (0.01)	0.134 (0.1)	1185.2 (0.000)	6.11	0.0057	0.59
IMF.2	−18.54 (0.01)	0.035 (0.1)	1400.9 (0.000)	6.38	0.0201	0.85
IMF.3	−15.65 (0.01)	0.017 (0.1)	402.6 (0.000)	4.81	−0.0100	1.22
IMF.4	−7.751 (0.01)	0.212 (0.1)	1283.4 (0.000)	6.21	−0.0380	2.53
IMF.5	−7.084 (0.01)	1.806 (0.1)	3266.4 (0.000)	8.05	−1.1880	8.85
IMF.6	−2.993 (0.15)	2.168 (0.01)	1347.2 (0.000)	5.34	1.1660	7.97
IMF.7	−1.914 (0.61)	0.506 (0.04)	86.03 (0.951)	2.42	−0.426	4.50
IMF.8	−3.090 (0.11)	1.694 (0.01)	195.00 (0.000)	1.97	−1.026	8.96
RES	−2.871 (0.20)	14.435 (0.01)	191.58 (0.000)	1.75	79.810	19.36

[a] Alternative hypothesis: Data is stationary
[b] Null hypothesis: Data is level stationary

TABLE 5
THE SET OF SIGNIFICANT REGRESSORS DETECTED FOR EACH IMF/RESIDUE OF WTI, WITH THE BN-QRL-BLASSO-BRR TECHNIQUES

Name	Method	Significant external regressors detected
IMF.1	BN (Constrained)	aroon, CCI, RSI, SMA
	BN (Scored)	aroon, CCI, RSI, SMA
	QRL	aroon, CCI
	BLasso	aroon, CCI, DEMA, RSI, SMA
	BRR	aroon, CCI, DEMA, RSI, SMA
IMF.2	BN (Constrained)	DEMA, EMA, MACD, RSI, TRIX
	BN (Scored)	DEMA, MACD, RSI, TRIX
	QRL	aroon, CCI, TDI
	BLasso	CCI, MACD, RSI, TRIX, VIX
	BRR	DEMA, EMA, MACD, RSI, SMA, TRIX, VIX
IMF.3	BN (Constrained)	aroon, CCI, DEMA, MACD, OVX, RSI, SMA, TDI, VIX
	BN (Scored)	aroon, CCI, DEMA, MACD, OVX, RSI, SMA, TDI, VIX
	QRL	aroon, CCI, TDI
	BLasso	aroon, CCI, DEMA, EMA, MACD, OVX, RSI, SMA, TDI, TRIX, VIX
	BRR	aroon, CCI, DEMA, EMA, MACD, OVX, RSI, SMA, TDI, TRIX
IMF.4	BN (Constrained)	aroon, MACD, RSI, TDI
	BN (Scored)	aroon, MACD, TDI
	QRL	aroon, CCI, TDI
	BLasso	aroon, DEMA, EMA, MACD, RSI, SMA, TDI, TRIX, VIX
	BRR	aroon, DEMA, EMA, MACD, RSI, SMA, TDI
IMF.5	BN (Constrained)	DEMA, MACD, SMA, TDI, OVX, VIX
	BN (Scored)	DEMA, MACD, SMA, TDI, OVX, VIX
	QRL	aroon, CCI, DEMA, EMA, TDI
	BLasso	aroon, CCI, DEMA, EMA, MACD, OVX, RSI, SMA, TDI, TRIX, VIX
	BRR	DEMA, EMA, MACD, OVX, RSI, SMA, TDI
IMF.6	BN (Constrained)	MACD, OVX, SMA, TDI, TRIX, VIX
	BN (Scored)	MACD, OVX, SMA, TDI, TRIX, VIX
	QRL	CCI, DEMA, VIX
	BLasso	DEMA, EMA, MACD, OVX, RSI, SMA, TDI, TRIX, VIX
	BRR	DEMA, EMA, MACD, OVX, RSI, SMA, TDI, TRIX, VIX

IMF.7	BN (Constrained)	MACD, RSI, TRIX, OVX, VIX
	BN (Scored)	MACD, RSI, TRIX, OVX, VIX
	QRL	aroon, CCI, DEMA, OVX, TDI
	BLasso	CCI, DEMA, EMA, OVX, SMA, TDI, VIX
	BRR	CCI, DEMA, EMA, OVX, SMA, TDI, TRIX, VIX
RES	BN (Constrained)	aroon, MACD, OVX, RSI, TDI, TRIX, VIX
	BN (Scored)	aroon, MACD, OVX, RSI, TDI, TRIX, VIX
	QRL	arron, CCI, EMA, TDI, VIX
	BLasso	aroon, DEMA, MACD, OVX, SMA, TDI, TRIX, VIX
	BRR	aroon, DEMA, MACD, OVX, SMA, TDI, TRIX, VIX

TABLE 6
THE FINAL SET OF EXTERNAL REGRESSORS FOR EACH IMF/RESIDUE OF WTI

Name	Significant external regressors
IMF.1	aroon, CCI, DEMA, RSI, SMA
IMF.2	aroon, CCI, DEMA, EMA, MACD, RSI, SMA, TDI, TRIX, VIX
IMF.3	aroon, CCI, DEMA, EMA, MACD, OVX, RSI, SMA, TDI, TRIX, VIX
IMF.4	aroon, CCI, DEMA, EMA, MACD, RSI, SMA, TDI, TRIX, VIX
IMF.5	aroon, CCI, DEMA, EMA, MACD, OVX, RSI, SMA, TDI, TRIX, VIX
IMF.6	CCI, DEMA, EMA, MACD, OVX, RSI, SMA, TDI, TRIX, VIX
IMF.7	aroon, CCI, DEMA, EMA, MACD, OVX, RSI, TDI, TRIX, VIX
RES	aroon, CCI, DEMA, EMA, MACD, OVX, RSI, TDI, TRIX, VIX

TABLE 7
THE FINAL SET OF EXTERNAL REGRESSORS FOR EACH IMF/RESIDUE OF BRENT

Name	Significant external regressors
IMF.1	aroon, CCI, EMA, MACD, RSI, SMA, VIX
IMF.2	aroon, CCI, DEMA, MACD, TRIX
IMF.3	aroon, CCI, DEMA, EMA, MACD, OVX, RSI, SMA, TDI, TRIX, VIX
IMF.4	aroon, CCI, MACD, RSI, SMA, TDI, TRIX
IMF.5	aroon, CCI, DEMA, EMA, MACD, OVX, RSI, VIX
IMF.6	CCI, DEMA, EMA, MACD, OVX, SMA, TDI, TRIX, VIX
IMF.7	aroon, CCI, DEMA, MACD, OVX, RSI, TDI, VIX
RES	aroon, CCI, EMA, MACD, OVX, RSI, TRIX, VIX

TABLE 8
THE FINAL SET OF EXTERNAL REGRESSORS FOR EACH IMF/RESIDUE OF ORB

Name	Significant external regressors
IMF.1	aroon, CCI, DEMA, EMA, RSI, SMA, TRIX
IMF.2	aroon, CCI, DEMA, MACD, SMA, TDI, TRIX
IMF.3	aroon, CCI, DEMA, EMA, MACD, OVX, RSI, SMA, TDI, TRIX, VIX
IMF.4	aroon, CCI, EMA, MACD, OVX, RSI, TRIX, VIX
IMF.5	aroon, CCI, DEMA, MACD, OVX, RSI, TDI, TRIX, VIX
IMF.6	CCI, DEMA, EMA, MACD, OVX, RSI, SMA, TDI, TRIX, VIX
IMF.7	CCI, DEMA, OVX, TDI, VIX
RES	aroon, CCI, DEMA, EMA, MACD, OVX, SMA, TDI, TRIX, VIX

TABLE 9

THE AVERAGE ERRORS OF THE 10-DAYS-AHEAD FORECASTS OF WTI

Name	MAE	RMSE	MAPE (%)
Method-1	1.75	2.13	0.03
Method-2	1.79	2.16	0.03
Method-3	2.58	3.32	0.04
Method-4	3.02	3.37	0.05
Method-5	1.87	2.34	0.03
Method-6	0.95	1.17	0.01
Method-7	1.28	1.52	0.02
Method-8	7.26	7.88	0.12
Method-9	1.92	2.14	0.03
Method-10	0.75	0.81	0.01S

TABLE 10
THE AVERAGE ERRORS OF THE 10-DAYS-AHEAD FORECASTS OF BRENT

Name	MAE	RMSE	MAPE (%)
Method-1	18.59	32.08	0.28
Method-2	18.79	32.14	0.29
Method-3	18.16	31.86	0.28
Method-4	20.17	33.23	0.32
Method-5	19.05	32.62	0.29
Method-6	0.96	1.19	0.01
Method-7	1.19	1.47	0.01
Method-8	19.98	23.91	0.30
Method-9	4.39	5.17	0.06
Method-10	0.96	1.20	0.01

TABLE 11
THE AVERAGE ERRORS OF THE 10-DAYS-AHEAD FORECASTS OF ORB

Name	MAE	RMSE	MAPE (%)
Method-1	0.74	0.89	0.01
Method-2	1.29	1.42	0.01
Method-3	3.07	3.17	0.04
Method-4	2.06	2.25	0.03
Method-5	0.68	0.82	0.01
Method-6	0.55	0.63	0.00
Method-7	0.91	1.06	0.01
Method-8	23.60	26.96	0.36
Method-9	2.97	3.56	0.04
Method-10	0.49	0.58	0.00

TABLE 12

THE DIEBOLD-MARIANO STATISTICS FOR 10-DAY FORECAST OF WTI/BRENT/ORB, FOR THE ALTERNATIVE HYPOTHESIS THAT METHOD-10 IS BETTER IN TERMS OF ACCURACY VERSUS THE METHOD OF CHOICE

	WTI	BRENT	ORB
Method-1	1.93 (0.04)	1.39 (0.09)	1.45 (0.08)
Method-2	1.99 (0.03)	1.39 (0.09)	2.80 (0.01)
Method-3	2.17 (0.02)	1.38 (0.09)	5.89 (0.00)
Method-4	3.32 (0.00)	1.44 (0.09)	3.47 (0.00)
Method-5	1.85 (0.04)	1.41 (0.08)	1.55 (0.07)
Method-6	1.05 (0.01)	0.06 (0.10)	0.33 (0.03)
Method-7	2.20 (0.02)	0.87 (0.20)	1.90 (0.04)
Method-8	4.56 (0.00)	2.35 (0.02)	3.06 (0.00)
Method-9	2.70 (0.01)	2.48 (0.01)	3.14 (0.00)

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TRANSLATED VERSION: SPANISH

Below is a rough translation of the insights presented above. This was done to give a general understanding of the ideas presented in the paper. Please excuse any grammatical mistakes and do not hold the original authors responsible for these mistakes.

VERSION TRADUCIDA: ESPAÑOL

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INTRODUCCIÓN

El precio del crudo tiene un papel fundamental en la economía mundial y sigue siendo el núcleo de los mercados energéticos. Como tal, sus fluctuaciones tienen el potencial de impactar la evolución económica en todo el mundo. La capacidad de pronosticar el precio del crudo es, por lo tanto, una herramienta útil en la gestión de la mayoría de los sectores industriales (Shin et al. 2013). Sin embargo, la previsión de los precios del crudo ha sido una tarea difícil, debido a su complejo comportamiento resultante de la influencia confluente de varios factores en el mercado del crudo. En concreto, las características no lineales exhibidas en la dinámica de las volatilidades de los precios del petróleo presentan un dilema para las técnicas predictivas, haciendo que la cuestión de la previsión de precios crudos (a largo plazo) esté abierta a la investigación financiera.

Existe una gran cantidad de literatura sobre el tema de la previsión de los precios del crudo. Estos artículos son innumerables, tanto en términos de los tipos de modelos como del número de métodos que se utilizan simultáneamente. Algunos estudios utilizan un enfoque con un único método (no híbrido) y otros se definen mediante varios métodos (híbridos). En este sentido, la heteroskedasticidad condicional autoregresiva generalizada (GARCH) fue uno de los primeros métodos utilizados debido a su capacidad para capturar varianza o volatilidad variable (Agnolucci 2009; 2012; Cheong 2009; 2008a; Hou y Suardi 2012; 2009; Mohammadi y Su 2010; Narayan y Narayan 2007; Sadorsky 2006; 2010). Intentamos realizar el modelo GARCH como un método híbrido mediante la combinación con otros modelos, como el modelo de volatilidad estocástica (SV), el modelo de volatilidad implícita (IV) y el modelo de máquina vectorial de soporte (SVM).

El método de la red neuronal (NNET) ha sido otro enfoque para la previsión de precios crudos (Azadeh et al. 2012; Ghaffari y Zare 2009; 2011; 2013; 2012; Yu et al. 2008; 2008). Sin embargo, según se informa, tiene la desventaja de sobreaquisar, mínimos locales y débil capacidad de generalización (Zhang et al. 2015). Por este bien, su uso híbrido se ha recomendado para los fines de la previsión de precios crudos.

Algunos autores optaron por utilizar el modelo SVM para la predicción de precios, aprovechando su idoneidad para modelar muestras de datos de pequeño tamaño con un comportamiento no lineal (Guo et al. 2012). Otros han informado sobre los méritos de la técnica de las ondas para la previsión de precios crudos (Yousefi et al. 2005) con una deficiencia importante es su sensibilidad al tamaño de la muestra. Sin embargo, la literatura reciente aboga por el uso de métodos híbridos para mejorar la precisión de la previsión de precios. El uso de lo mejor de cada técnica en un marco híbrido se ha mejorado combinando el método de computación suave o econométrica o ambos (Fan et al. 2008b; 2013). (2015) se remite al lector para una evaluación más completa de las investigaciones anteriores sobre la previsión de precios del petróleo.

La motivación detrás del trabajo actual fue explotar el potencial de la teoría de la red bayesiana (BN), en el contexto de la predicción de precios crudos, mediante la construcción de una red sobre componentes de precios descompuestos. Como tal, el presente artículo contribuye a la literatura existente en este campo proponiendo un nuevo método híbrido dentro de un marco de red bayesiana. Además, este artículo informa de los resultados de otros métodos híbridos ideados, utilizando Random Forest (RF), Markov Chain Monte Carlo (MCMC), NNET y SVM. El resto del artículo se organiza de la siguiente manera. En la siguiente sección se detallarán los métodos que se utilizan. En la tercera sección se proporciona una descripción de los resultados, a la que seguirán algunas observaciones finales.

CONCLUSIÓN

El rendimiento de la propuesta de red bayesiana híbrida fue excepcional en comparación con los otros modelos híbridos ideados, en todos los tres tipos de precios crudos (WTI, BRENT y ORB) y con los tres puntos de referencia estadísticos (MAE, RMSE y MAPE). El BN demostró que los índices de volatilidad (OVX, VIX) influyen en las diferentes señales descompuestas del precio del crudo, afectando a los valores de precios de nivel por delante. Se demostró que el poder predictivo de los métodos híbridos que adoptan GARCH era inferior a los otros métodos, que aplican regresiones a todas las capas de la señal descompuesta para la previsión de precios crudos. Dado que el método híbrido propuesto hace uso de regresores con períodos de vida a corto plazo (es decir, indicadores técnicos, OVX, VIX y valores de precios pasados), el método sigue siendo una opción válida para la previsión a corto plazo. La cuestión de su capacidad en el manejo de las previsiones de precios a largo plazo aún no ha sido respondida por la investigación futura utilizando parámetros con viabilidad a largo plazo.

TRANSLATED VERSION: FRENCH

Below is a rough translation of the insights presented above. This was done to give a general understanding of the ideas presented in the paper. Please excuse any grammatical mistakes and do not hold the original authors responsible for these mistakes.

VERSION TRADUITE: FRANÇAIS

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INTRODUCTION

Le prix du pétrole brut joue un rôle central dans l'économie mondiale et demeure au cœur des marchés de l'énergie. En tant que tel, ses fluctuations ont le potentiel d'avoir un impact sur les développements économiques dans le monde entier. La capacité de prévoir le prix du pétrole brut est donc un outil utile dans la gestion de la plupart des secteurs industriels (Shin et al., 2013). Néanmoins, la prévision des prix du pétrole brut a été une tâche difficile, en raison de son comportement complexe résultant de l'influence confluente de plusieurs facteurs sur le marché du pétrole brut. En particulier, les caractéristiques non lignenaires exposées dans la dynamique des volatilités des prix du pétrole présentent un dilemme pour les techniques prédictives, rendant la question des prévisions des prix du brut (à long terme) ouverte au financement de la recherche.

Il existe une mine de documentation sur la prévision des prix du pétrole brut. Ces articles sont innombrables, tant en termes de types de modèles que de nombre de méthodes utilisées simultanément. Certaines études utilisent une approche avec une seule méthode (non hybride) et d'autres sont définies par plusieurs méthodes (hybrides). À cet égard, l'hétéroskedasticité conditionnelle autorégressive généralisée (GARCH) a été parmi les premières méthodes utilisées en raison de sa capacité à capturer la variance ou la volatilité variable dans le temps (Agnolucci 2009; Arouri et coll. 2012; Cheong, 2009; Fan et coll. 2008a; Hou et Suardi 2012; Kang et coll. 2009; Mohammadi et Su, 2010; Narayan et Narayan, 2007; Sadorsky, 2006; Wei et coll. 2010). Nous avons essayé d'exécuter le modèle GARCH comme méthode hybride en combinant avec d'autres modèles, tels que le modèle de volatilité stochastique (SV), le modèle de volatilité implicite (IV) et le modèle de machine vectorielle de soutien (SVM).

La méthode du réseau neuronal (NNET) a été une autre approche pour la prévision des prix du brut (Azadeh et al., 2012; Ghaffari et Zare, 2009; Movagharnejad et coll. 2011; Shin et coll. 2013; Wang et coll. 2012; Yu et coll. 2008; Zhang et coll. 2008). Toutefois, elle aurait l'inconvénient d'un surajustage, de minima locaux et d'une faible capacité de généralisation (Zhang et al., 2015). Pour cette raison, son utilisation hybride a été recommandée aux fins de la prévision des prix du brut.

Certains auteurs ont choisi d'utiliser le modèle SVM pour la prévision des prix, profitant de sa pertinence pour modéliser des échantillons de données de petite taille ayant un comportement non ligneux (Guo et coll., 2012). D'autres ont fait rapport sur les mérites de la technique des ondes pour la prévision des prix du brut (Yousefi et coll., 2005), l'une des principales lacunes étant sa sensibilité à la taille de l'échantillon. Toutefois, la littérature récente préconise l'utilisation de méthodes hybrides pour améliorer l'exactitude des prévisions de prix. L'utilisation du meilleur de chaque technique dans un cadre hybride a été améliorée en combinant la méthode soft-computing ou économétrique ou les deux (Fan et coll. 2008b; Xiong et coll. 2013). Le lecteur est renvoyé à l'excellent examen par Zhang et coll. (2015) pour une évaluation plus complète des recherches antérieures sur la prévision des prix du pétrole.

La motivation derrière les travaux actuels était d'exploiter le potentiel de la théorie du réseau bayésien (BN), dans le contexte de la prévision des prix du brut, en construisant un réseau sur les composantes de prix décomposées. À ce titre, le présent article contribue à la littérature existante dans ce domaine en proposant une nouvelle méthode hybride dans un cadre de réseau bayésien. En outre, cet article rapporte les résultats sur d'autres méthodes hybrides conçues, en utilisant Random Forest (RF), Markov Chain Monte Carlo (MCMC), NNET et SVM. Le reste de l'article est organisé comme suit. La section suivante détaillera les méthodes utilisées. Une description des résultats est fournie dans la troisième section, qui sera suivie de quelques remarques finales.

CONCLUSION

La performance de la proposition de réseau hybride bayésien a été exceptionnelle par rapport aux autres modèles hybrides conçus, dans les trois types de prix bruts (WTI, BRENT et ORB) et par rapport aux trois indices de référence statistiques (MAE, RMSE et MAPE). Le BN a démontré que les indices de volatilité (OVX, VIX) ont une influence sur les différents signaux décomposés du prix du brut, affectant les valeurs des prix à l'avance. La puissance prédictive des méthodes hybrides adoptant garch s'est montrée inférieure aux autres méthodes, qui appliquent des régressions à toutes les couches du signal décomposé pour la prévision des prix bruts. Étant donné que la méthode hybride proposée utilise des régresseurs dont la durée de vie est à court terme (c.-à-d. Les indicateurs techniques, OVX, VIX et les valeurs de prix passées), la méthode demeure une option valable pour les prévisions à court terme. La question de sa capacité à gérer les prévisions de prix à long terme n'a pas encore été résolue par la recherche future en utilisant des paramètres de viabilité à long terme.

TRANSLATED VERSION: GERMAN

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ÜBERSETZTE VERSION: DEUTSCH

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EINLEITUNG

Der Rohölpreis spielt eine zentrale Rolle in der Weltwirtschaft und bleibt im Kern der Energiemärkte. Daher haben seine Schwankungen das Potenzial, die wirtschaftliche Entwicklung weltweit zu beeinflussen. Die Fähigkeit, den Rohölpreis vorherzusagen, ist daher ein nützliches Instrument für die Verwaltung der meisten Industriesektoren (Shin et al. 2013). Dennoch war die Prognose der Rohölpreise aufgrund ihres komplexen Verhaltens, das sich aus dem einflussvon mehreren Faktoren auf den Rohölmarkt ergibt, eine schwierige Aufgabe. Insbesondere stellen die nichtlinearen Merkmale, die in der Dynamik der Ölpreisvolatilitäten zu sehen sind, ein Dilemma für Vorhersagetechniken dar, was die Frage der (langfristigen) Rohpreisprognosen für die Finanzforschung offen macht.

Zum Thema Prognose der Rohölpreise gibt es eine Fülle von Literatur. Diese Artikel sind myriad, sowohl in Bezug auf die Arten von Modellen und die Anzahl der Methoden, die gleichzeitig verwendet werden. Einige Studien verwenden einen Ansatz mit einer einzigen Methode (nicht-hybrid) und einige werden durch mehrere Methoden (Hybrid) definiert. In dieser Hinsicht gehörte die generalisierte autoregressive bedingte Heteroskedastizität (GARCH) zu den ersten Methoden, die aufgrund ihrer Fähigkeit verwendet wurden, zeitverändernde Varianz oder Volatilität zu erfassen (Agnolucci 2009; Arouri et al. 2012; Cheong 2009; Fan et al. 2008a; Hou und Suardi 2012; Kang et al. 2009; Mohammadi und Su 2010; Narayan und Narayan 2007; Sadorsky 2006; Wei et al. 2010). Wir haben versucht, das GARCH-Modell als Hybridmethode durchzuführen, indem wir mit anderen Modellen kombiniert wurden, wie dem Stochastischen Volatilitätsmodell (SV), dem Modell der impliziten Volatilität (IV) und dem St.-AD-Modell (Support Vector Machine).

Die Methode des neuronalen Netzwerks (NNET) war ein weiterer Ansatz für die Rohpreisvorhersage (Azadeh et al. 2012; Ghaffari und Zare 2009; Movagharnejad et al. 2011; Shin et al. 2013; Wang et al. 2012; Yu et al. 2008; Zhang et al. 2008). Es trägt jedoch angeblich den Nachteil von überfitting, lokalen Minima und schwachen Verallgemeinerungsfähigkeit (Zhang et al. 2015). Um dies zu wollen, wurde seine hybride Verwendung für die Zwecke der Rohpreisvorhersage empfohlen.

Einige Autoren entschieden sich für das SVM-Modell zur Preisvorhersage und nutzten seine Eignung für die Modellierung kleiner Datenstichproben mit nichtlinearem Verhalten (Guo et al. 2012). Andere haben über die Vorzüge der Wavelet-Technik für die Rohpreisvorhersage (Yousefi et al. 2005) berichtet, wobei ein großes Manko seine Empfindlichkeit gegenüber der Stichprobengröße ist. Die jüngste Literatur setzt sich jedoch für den Einsatz hybrider Methoden ein, um die Genauigkeit der Preisprognosen zu verbessern. Die Verwendung der besten jeder Technik in einem hybriden Framework wurde durch die Kombination der Soft-Computing- oder ökonometrischen Methode oder beides verbessert (Fan et al. 2008b; Xiong et al. 2013). Der Leser wird auf die ausgezeichnete Rezension von Zhang et al. (2015) für eine vollständigere Bewertung vergangener Forschungen über Ölpreisprognosen verwiesen.

Die Motivation hinter der gegenwärtigen Arbeit war, das Potenzial der Bayesschen Netzwerktheorie (BN) im Kontext der Rohpreisvorhersage zu nutzen, indem ein Netzwerk über zersetzten Preiskomponenten gebaut wurde. Als solcher trägt der vorliegende Artikel zur bestehenden Literatur auf diesem Gebiet bei, indem er eine neuartige hybride Methode innerhalb eines bayesischen Netzwerkrahmens vorschlägt. Darüber hinaus berichtet dieser Artikel Überergebnisse zu anderen entwickelten Hybridmethoden mit Random Forest (RF), Markov Chain Monte Carlo (MCMC), NNET und SVM. Der Rest des Artikels ist wie folgt organisiert. Im nächsten Abschnitt werden die verwendeten Methoden erläutert. Eine Beschreibung der Ergebnisse ist im dritten Abschnitt enthalten, dem einige abschließende Bemerkungen folgen werden.

SCHLUSSFOLGERUNG

Die Leistung des hybriden Bayesschen Netzwerkangebots war im Vergleich zu den anderen entwickelten Hybridmodellen in allen drei Rohpreistypen (WTI, BRENT und ORB) und gegenüber allen drei statistischen Benchmarks (MAE, RMSE und MAPE) hervorragend. Der BN zeigte, dass die Volatilitätsindizes (OVX, VIX) Einfluss auf verschiedene zersetzte Signale des Rohölpreises haben, was sich auf die Preiswerte auswirkt. Die Vorhersagekraft der hybriden Methoden, die GARCH anwenden, erwies sich als schlechter als die anderen Methoden, die Regressionen auf alle Schichten des zersetzten Signals für die Rohpreisprognose anwenden. Da die vorgeschlagene Hybridmethode Regressoren mit kurzfristigen Lebensdauern (d. H. Technische Indikatoren, OVX, VIX und frühere Preiswerte) verwendet, bleibt die Methode eine gültige Option für kurzfristige Prognosen. Die Frage nach ihrer Fähigkeit, langfristige Preisprognosen zu handhaben, muss die künftige Forschung mit Parametern mit längerfristigem Lebensfähigkeitnoch beantworten.

TRANSLATED VERSION: PORTUGUESE

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VERSÃO TRADUZIDA: PORTUGUÊS

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INTRODUÇÃO

O preço do petróleo bruto tem um papel fundamental na economia global e mantém-se no centro dos mercados energéticos. Como tal, as suas flutuações têm o potencial de impactar a evolução económica em todo o mundo. A capacidade de prever o preço do petróleo bruto é, portanto, uma ferramenta útil na gestão da maioria dos sectores industriais (shin et al. 2013). No entanto, a previsão dos preços do petróleo bruto tem sido uma tarefa desafiante, devido ao seu comportamento complexo resultante da influência confluente de vários fatores no mercado do petróleo bruto. Em particular, as características não lineares expostas na dinâmica das volatilidades dos preços do petróleo apresentam um dilema para técnicas preditivas, tornando a questão da previsão de preços brutos (a longo prazo) aberta ao financiamento da investigação.

Existe uma riqueza de literatura sobre o tema da previsão dos preços do petróleo bruto. Estes artigos são miríades, tanto em termos dos tipos de modelos como do número de métodos utilizados simultaneamente. Alguns estudos utilizam uma abordagem com um único método (não-híbrido) e alguns são definidos por vários métodos (híbridos). A este respeito, a heterosquestza condicional generalizada autoregressiva (garch) foi um dos primeiros métodos utilizados devido à sua capacidade de capturar variações ou volatilidade variáveis no tempo (agnolucci 2009; arouri et al. 2012; cheong 2009; fan et al. 2008a; hou e suardi 2012; kang et al. 2009; mohammadi e su 2010; narayan e narayan 2007; sadorsky 2006; wei et al. 2010). Tentámos executar o modelo garch como um método híbrido, combinando com outros modelos, como o modelo de volatilidade estocástica (sv), o modelo de volatilidade implícita (iv) e o modelo de máquina vetorial de suporte (svm).

O método da rede neural (nnet) foi outra abordagem para a previsão dos preços do crude (azadeh et al. 2012; ghaffari e zare 2009; movagharnejad et al. 2011; shin et al. 2013; wang et al. 2012; yu et al. 2008; zhang et al. 2008). No entanto, alegadamente, tem a desvantagem de excesso de adaptação, minima local e fraca capacidade de generalização (zhang et al. 2015). Para tal, a sua utilização híbrida foi recomendada para efeitos de previsão dos preços brutos.

Alguns autores optaram por utilizar o modelo svm para a previsão de preços, tirando partido da sua adequação para modelar amostras de dados de pequena dimensão com comportamento não linear (guo et al. 2012). Outros relataram os méritos da técnica de onda para a previsão dos preços brutos (yousefi et al. 2005) com uma grande lacuna sendo a sua sensibilidade ao tamanho da amostra. No entanto, a literatura recente defende a utilização de métodos híbridos para melhorar a exatidão da previsão dos preços. A utilização do melhor de cada técnica num quadro híbrido foi reforçada combinando o método de computação suave ou econométrico ou ambos (fan et al. 2008b; xiong et al. 2013). O leitor é referido à excelente revisão por zhang et al. (2015) para uma avaliação mais completa de pesquisas passadas sobre a previsão do preço do petróleo.

A motivação subjacente ao presente trabalho foi explorar o potencial da teoria da rede bayesiana (bn), no contexto da previsão dos preços brutos, construindo uma rede sobre componentes de preços decompostos. Como tal, o presente artigo contribui para a literatura existente neste domínio, propondo um novo método híbrido dentro de um quadro de rede bayesiano. Além disso, este artigo relata resultados de outros métodos híbridos concebidos, utilizando a random forest (rf), markov chain monte carlo (mcmc), nnet e svm. O resto do artigo é organizado da seguinte forma. A secção seguinte irá detalhar os métodos utilizados. Uma descrição dos resultados é fornecida na terceira secção, que será seguida de algumas observações finais.

CONCLUSÃO

O desempenho da proposta híbrida da rede bayesiana foi notável em comparação com os outros modelos híbridos concebidos, em todos os três tipos de preços brutos (wti, brent e orb) e contra todos os três referenciais estatísticos (mae, rmse e mape). O bn demonstrou que os índices de volatilidade (ovx, vix) são influentes em diferentes sinais decompostos do preço do crude, afetando os valores de preços de nível futuro. O poder preditivo dos métodos híbridos que adotam a garch mostrou-se inferior aos outros métodos, que aplicam regressões a todas as camadas do sinal decomposto para a previsão dos preços brutos. Uma vez que o método híbrido proposto utiliza os regressos com prazos de vida de curta duração (isto é, indicadores técnicos, ovx, vix e valores de preços anteriores), o método continua a ser uma opção válida para a previsão a curto prazo. A questão da sua capacidade de lidar com as previsões de preços a longo prazo ainda está por responder pela futura investigação utilizando parâmetros com viabilidade a longo prazo.