Blockchain Transaction Fee Forecasting

Conall Butler

School of Computing
Dublin City University
21269599

Bhavesh Bhagria

School of Computing
Dublin City University
21262891

Jitesh Jhawar

School of Computing
Dublin City University
21264999

Abstract: The generation of cryptocurrency happens **through mining. A lot of computing power and electricity is utilised for mining of cryptocurrency. The computing power cost associated with transactions on the Ethereum, and other cryptocurrency networks is called gas price. As the increasing mining of cryptocurrency leads to increase in power consumption and further environmental losses, it is necessary to monitor and predict gas price costs. In this paper we investigate the gas price using pre-processing, data mining and time series modelling techniques toward gaining insight into and modelling of Ethereum network gas price time series is proposed. Wavelet transform, matrix profile algorithms and data structures, and attention-LSTM time series modelling are the methods of interest. A Direct-Recursive hybrid LSTM model was implemented with forecast up to a 50 minute lookahead showing minimal degradation of evaluation metrics with increasing overcast horizon.**

Repo: github.com/ConallButler/CA683--Blockchain-Transaction-Fee-Forecasting

Keywords: Data Mining, Forecasting, Data Manipulation, Cryptocurrency.

Introduction

The potentially disruption and innovation through Blockchain technologies and applications, such as DeFi (Decentralized Finance), Non-Fungible Tokens (NFTs), cryptocurrencies and smart contracts, is a much-discussed topic. Ether (ETH) is the second largest cryptocurrency by market cap, and its associated blockchain, Ethereum, enables development of these decentralized applications through the Ethereum Virtual Machine. Use of the network is growing, with number of daily transactions rising from 500,000 to 1,300,000 between 2018 and 2021.[1]

Transactions on the Ethereum Network are defined as cryptographically signed instructions between accounts. These instructions can range from simple transfer of ETH to more complex contract deployments. Gas is the unit of computational work done processing a transaction on the network. Transactions consume a number of gas units depending on their computational intensity. Senders of transactions submit a price per unit of gas, in ETH, when submitting their transactions. Miners are rewarded with a portion of this cost, and are free to select transactions with the most lucrative gas cost for inclusion in the blockchain, with the next mined block.[2] Miners have been shown to select transactions for mining primarily on gas cost.[3]

High gas fees are seen as a major setback to applications on the Ethereum Network. Popular gas price recommenders use simple heuristics and past data to generate a number of recommendations.

We propose a forecasting method for predicting Gas price for cryptocurrency. We intend to investigate the inclusion of an attention mechanism driven by matrix profile, contrary to some approaches that have used LSTM and GRU models. We will use a combination of wavelets transforms, Matrix profile and attention-LSTM methods towards time series forecasting, particularly in the domain of cryptocurrency transaction prices.

Related Work

A. Gas Price Mechanics

Donmez et al investigates the economic determinants of gas price based on blockchain and cryptocurrency exchange data. Marginal and median daily Gas price is found to have a strong non-linear association with block utilization, with particularly influence above a threshold of 90% utilization, and minimal price impact below 90%. Transaction type is also associated with gas price; ETH transfer transactions tend to be more urgent, and a higher proportion of transfer transaction over contract transactions is associated with higher gas price. ETH cryptocurrency price is also found to be negatively associated with gas price, consistent with the notion that network user are concerned with the transaction costs in terms of real currency value.[13]

Pierro et al apply granger causality toward investigation of the Influence factors of Ethereum transaction fees. They use Ether chain "Fast" gas price prediction as their gas price variable. This is the gas price at which 90% of the 200 previously mined blocks contain a transaction at or below the price. Transactions submitted at this gas price are estimated to be approved within 1-2 minutes. Pairwise granger causation of unconfirmed transaction count by gas price, and gas price by miner count is indicated at $p = 0.05$, with negative Pearson corelation in both cases. Of the other variables tested, ETH/USD, ETH/BTC, block difficulty, block time, and hash rate, none were found to share granger causality with the Etherchain gas price.[14] This indicates a multivariate model may be worth exploring

B. Gas Price Forecast Studies

Werner et al perform empirical analysis of historic data, and propose a gas price recommendation algorithm driven by a block-minimum gas price forecast generated by GRU network. Recommendations by the proposed algorithm and model are able to achieve a 75% saving with a 4.8 block increased wait time, as compared to the popular Go-Ethereum (Geth) recommender. Feeding the recommendation algorithm real future data, as opposed to a forecast, is used to generate an ideal recommendation; as there is some difference between the forecasted recommendation and the ideal, this indicates room for improvement in the forecasting model. High volatility in the gas price data is indicated by maximum gas price exceeding minimum gas price by an order of magnitude, average block gas price standard deviation of 46.46 Gwei with mean of 13.96 Gwei. Seasonality of gas price with lag of 24 hours is indicated by autocorrelation of 1 hour interval gas price averages. Down sampling to 5-minute resolution, outlier deletion based on standard deviation, and discrete Fourier-transform based denoising is applied to the data before modelling. This study provides a good exploratory baseline, and demonstrates possibility of multivariate modelling.

A sliding window approach with fixed number of timesteps as model inputs and fixed model output forecast length is iterated across the data to generate the forecast time series. [5, 15]

Mars et al compare GRU, LSTM and Facebook Prophet models with Geth recommendations for minimum gas price forecasts. A similar sliding window approach of previous 300 blocks an input, and the next block as output is used. GRU and LSTM have comparable performance, and outperform Geth and Prophet forecasts which are also comparable. Down sampling to 5-minute resolution, and outlier deletion based on standard deviation are also employed before RNN modelling as in Werner et al.[6] Mar perform extensive hyperparameter optimization, their model hyperparameters are compared with others in initial modelling.

Data Mining Methodology

Business Understanding – What does the business need?

*<u>Some means of informing what gas price to submit a transaction with</u>***.** There are many ways this question can be framed, this is evident in the variety of approaches taken by gas price recommenders such as Go Ethereum and Eth gas station, including probability-based approaches such as Poisson regression. An accurate forecast of gas price implicitly contains the answers to these problems, and can be used to make a decision on when in the forecast window will be the most cost-effective time to submit the transaction.

Minimum block gas price, the lowest gas price for any mined transaction in a block, is the parameter of interest for forecasting. This variable gives the best indication of the lower bound of gas price a transaction could be submitted with in order to be selected for mining.

Data understanding – What data do we have / need? Is it clean?

Data is clean, one issue is with variability in the time between blocks. Only Issues is with variable time between locks; solved by down sampling.

We have many time series that gas price has been identified in both literature and EDA as having a potential causal relationship; ETH exchange price, blockchain utilisation, we will test these in modelling.

A challenge in modelling will be the high degree of noise in the data, high level of variance, and non-constant level of variance.

What we need is the ability to forecast the minimum block gas price, with;

- A forecasting horizon long enough to give time for meaningful decision making.
- Accuracy sufficient to make the forecast meaningful.

Data preparation – How do we organize the data for modelling?

- Data retrieved by SQL query as CSV; we can get min/max/average block gas price with intelligent querying
- Down sampling to reduce impact of noise, and provide an evenly spaced time series.

Modelling – What modelling techniques should we apply?

- Wavelet coherence allows for visualisation of correlation between 2 time series, On the basis of a wavelet, a salient pattern in the data, at different time scales and frequency scales of the wavelet. Can be used to identify inputs.

- Commonly used time series forecasting strategies
  - ➢ Simple 1 Step lookahead
  - ➢ Recursive Forecast
  - ➢ Direct Multi-step ensemble
  - ➢ Direct-Recursive Hybrid
  - ➢ Multiple output

- A Matrix Profile driven attention mechanism can improve performance in Encoder-Decoder LSTM models
- Discrete wavelets transform can denoise signals; standard deviation above mean is evident in gas price data. May reduce impact of noise on forecast

Evaluation – Which model best meets the business objectives?

The initial intention was to use an Encoder-Decoder LSTM with an attention mechanism directed by Matrix Profile. Initial evaluation of an encoder-decoder showed poor results, as discussed. The degree of complexity in this type of model presented a risk in that no useful forecast may have been developed if the entire project was focused on this. The decision was made to focus on forecasting using simpler LSTM models. Wavelet denoising was also not used in final modelling, as sufficient complexity was present.

Single variate and multivariate 1 step lookahead models were first evaluated, and the best parameters then used to build the direct multi-step and hybrid ensemble models. This multi model approach eliminates the need any trade off short between and long-term forecasting performance; separate models are optimized for each timestep.

Deployment – How do stakeholders access the results?

Initial proof of concept delivered by this report, presentation. Dashboard could be developed to use trained models and real time blockchain, and exchange data to display forecasted gas price at different lookaheads, and expected errors of these lookaheads.

Evaluation/Results

Wavelet Coherence: Can we identify model inputs?

Fig1. Shows wavelet coherence minimum block gas price vs maximum block gas price, and minimum block gas price vs ETH/USD exchange price. Inclusion of ETH/USD as a variable in model s had a negative effect on performance, which coincides with the lack of coherence. In comparison, maximum gas price improved model performance when included as a variable. It cannot be said for certain if coherence can rule out a variable for modelling; complex models can learn complex dependencies that are not evident in coherence plots. However, on these relatively simple models, correlation on large time scales may be an indicator of predictability.

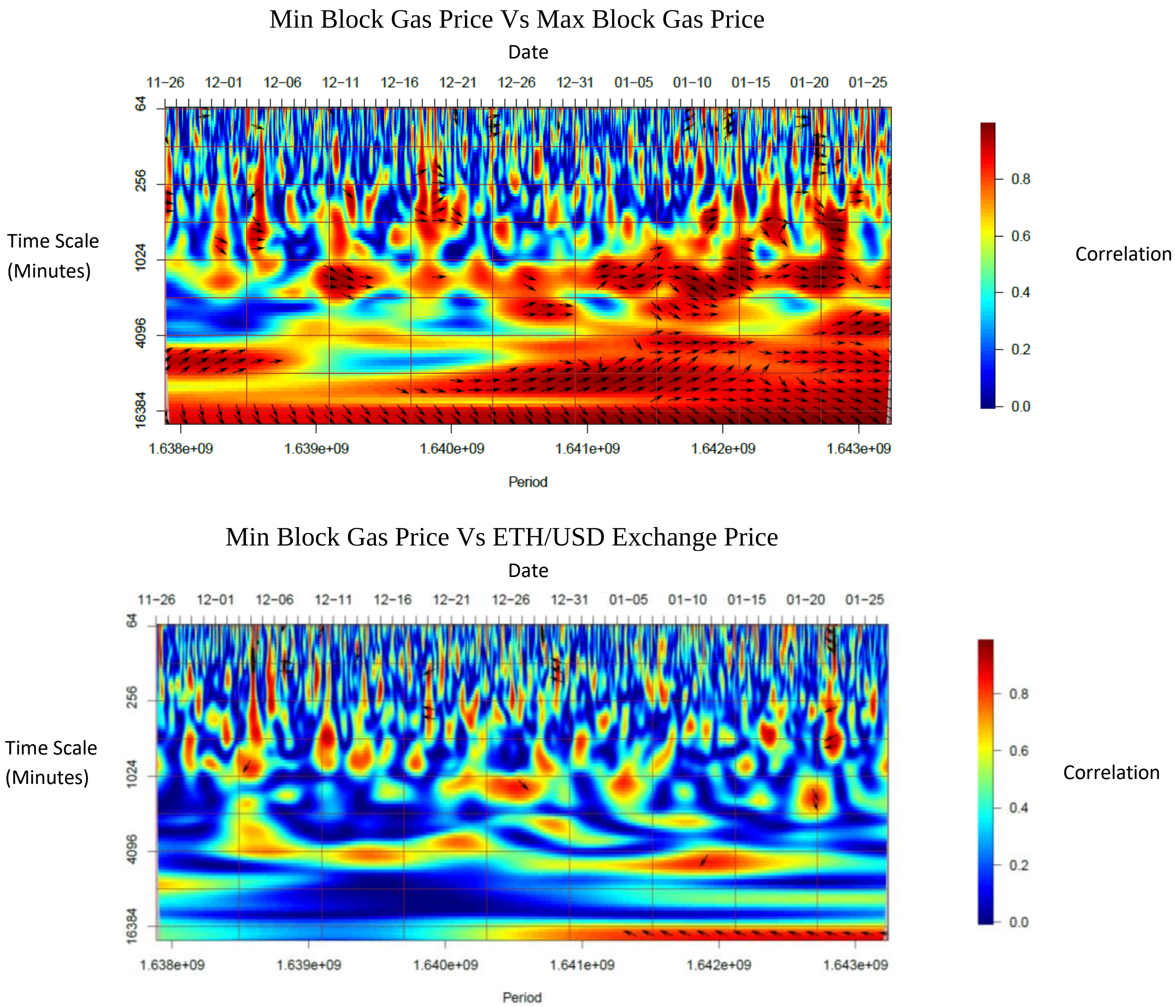

Fig 1. Wavelet coherence plots for i(Min block gas price vs Max Block Gas Price), ii(Max Block Gas price vs ETH/USD Exchange Price. Data sampled over 5 minute windows, Morlet mother wavelet.

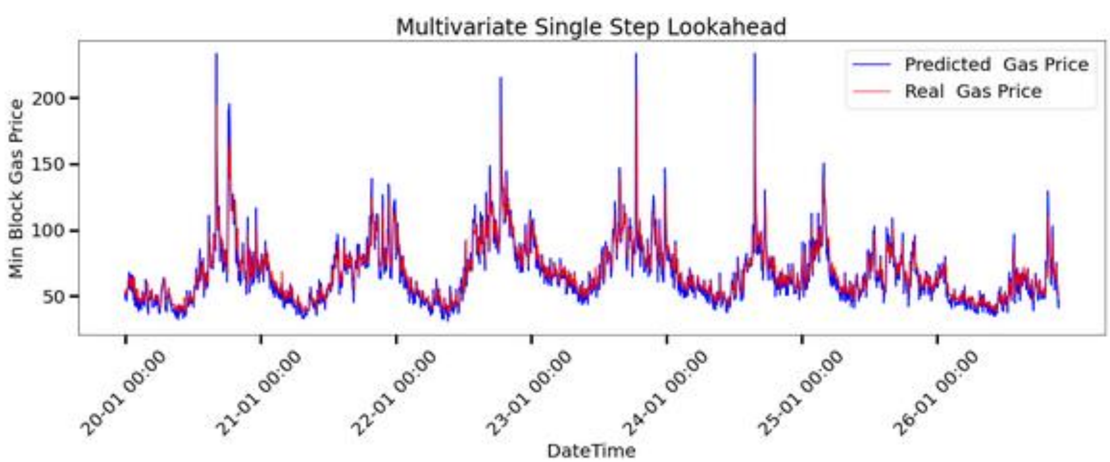

Fig 2. Forecast of Minimum Block Gas price, single timestep lookahead. Forecast made by multivariate single step lookahead model. Input variables were maximum block gas price, minimum block gas price, and its 24-hour lag.

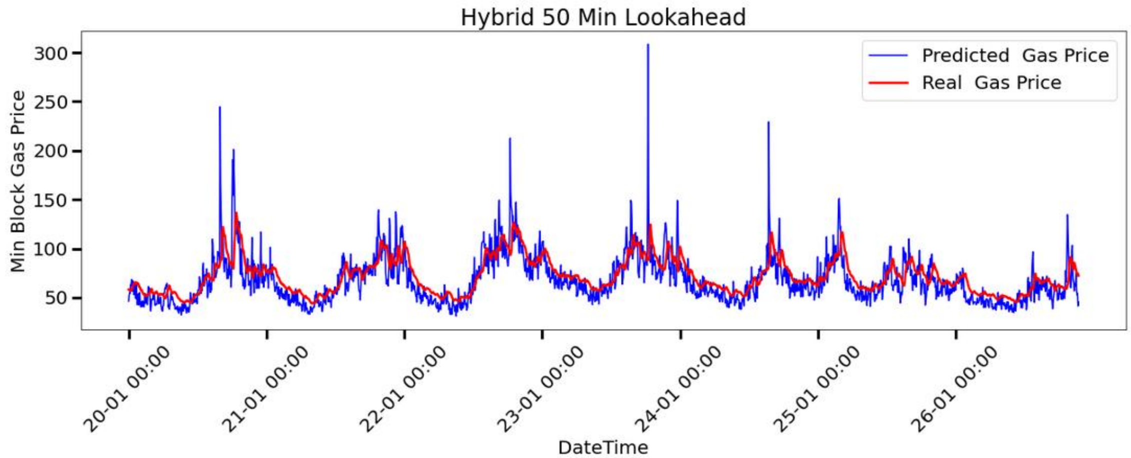

Fig 3. Forecast of Minimum Block Gas price, with a 50 minute lookahead, averaged over 5-minute window. Forecast made by the 10 step lookahead model in the univariate Direct-Recursive Hybrid Ensemble.

Table I

Direct-Recursive Hybrid Model

Lookahead	RMSE	MSE	MAE	MAPE	R2
5 min	227.4064	15.08	9.733	0.142	0.611
10 min	227.7081	15.09	9.763	0.143	0.61
15 min	228.9169	15.13	9.594	0.138	0.608
20 min	257.9236	16.06	11.28	0.174	0.558
25 min	268.96	16.4	10.828	0.158	0.54
30 min	266.0161	16.31	10.43	0.15	0.545
35 min	267.9769	16.37	10.054	0.138	0.541
40 min	272.9104	16.52	10.825	0.159	0.533
45 min	283.9225	16.85	10.777	0.153	0.514
50 min	300.3289	17.33	12.04	0.182	0.486

Table II

Direct Multistep Model, Mutlivariate

Lookahead	RMSE	MSE	MAE	MAPE	R2
5 min	152.05	12.33	7.97	0.119	0.740
10 min	236.76	15.39	9.94	0.146	0.595
15 min	289.00	17.00	11.04	0.159	0.505
20 min	320.13	17.89	11.65	0.167	0.452
25 min	345.99	18.60	12.20	0.175	0.408
30 min	366.46	19.14	12.60	0.180	0.373
35 min	381.58	19.53	12.81	0.183	0.347
40 min	386.87	19.67	13.03	0.187	0.338
45 min	389.43	19.73	13.15	0.189	0.333
50 min	389.93	19.75	13.34	0.193	0.333

Table III

Evaluation Metrics of 1 step lookahead models, varying Inputs and Hyperpararameters

Model	MSE	RMSE	MAE	MAPE	R2
Univariate, no limit	240.84	15.52	9.97	0.139	-
Univariate, 2 SD limit	224.10	14.97	9.72	0.142	-
Univariate, Mars changes, no	190.63	13.81	8.65	0.134	0.68
Univariate, Mars changes, 2 SD limit	170.30	13.05	8.09	0.121	**0.71**
Min, Max gas price, 2 SD limit	224.25	14.98	9.71	0.142	-
Min, Max gas price, no limits	191.41	13.84	8.62	0.132	0.676
Min, Max, 24Hr lag, no limits	187.58	13.70	8.20	0.121	0.688
Min, Max gas price, 2 no limit, Mars hyperparams.	230.89	15.20	7.45	0.174	0.608
Min, Max gas price, 2 SD limit, Mars hyperparams.	164.71	12.83	7.44	**0.104**	0.721
Min, Max, 24Hr lag, 2 SD limit, Mars hyperparams.	**132.83**	**11.53**	**7.40**	0.107	**0.764**
Min, Max, 24Hr lag, ETH/USD, 2 SD limit, Mars hyp.	146.42	12.10	7.45	0.107	0.749

Tables I and II show evaluation metrics for the two multi-step models considered. Table II shows evaluation metrics for the various single step models. Optimal hyperparameters as found by Mars et al [6] consistently outperform manually adjusted hyperparameters.

LSTM Models

Hyperparameters found to be optimal by Mars et al were found to outperform those set manually in both univariate and multivariate models. It is possible that given the different data used, and addition of new variables, and ensemble approaches used, that different model architectures and hyperparameters may have performed better than those found in Mars [6]. However, a full search of the hyperparameter space was decided to be out of scope for this project. Applying a limit of two standard deviations above the mean, to outliers for the minimum gas price data is an approach that is used in Werner and Mars towards gar price forecasting[5,6]. This was found to improve metrics in the univariate vase, with mixed results in the multivariate case.

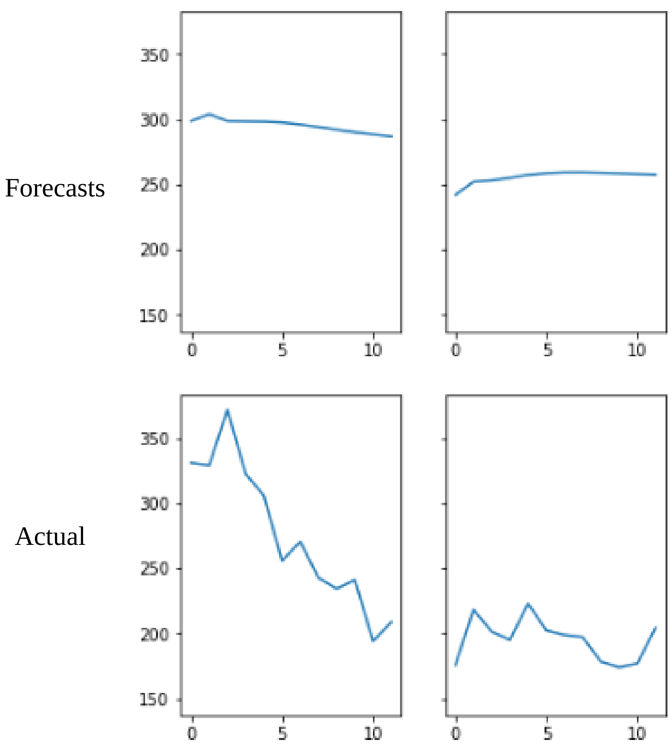

Fig 4. Example of typical forecasts by final Bottleneck Encoder-Decoder Model, forecasting 10 steps ahead.

The Direct-Recursive Hybrid model shows good maintenance of evaluation metrics with increasing forecast horizon, in comparison to the Direct Multivariate model which degraded quickly. No of epochs was reduced in the multi-model approaches, compared to the single step forecasts. A reduction in performance on the single step lookahead in the multi-step model can be seen as a results.

Forecasts typical of tested Encoder-Decoder models displayed in Fig 4. demonstrate an inability of the model to account for the noisy nature of the data. Several architectures and inputs were attempted, similar results were found in all. It is likely that better performance would be achievable with this approach with a full search of model architectures, parameters and inputs, however the risk of failure to deliver given the complexity of this approach was considered too great to warrant further pursuit.

Conclusions and future work

To conclude, a variety of model architectures were applied to gas price forecasting, with a Direct-Recursive Hybrid model showing good ability to maintain good forecasting metrics with increasing lookahead horizon, with mean absolute error only increasing by 3 units from 1 to 10 step lookahead. Wavelet coherence was shown to have some agreement with results found in modelling, in that high coherence series were found to improve model performance when included as inputs. Further work would investigate further hyperparameter optimization, Encoder-Decoder models, with a matrix profile attention mechanism, and use of wavelet denoised data. The complexity of even relatively simple LSTM models was highlighted; the importance of attempting relatively simple model architectures before attempting a complex model was highlighted.

References

[1] etherscan.io. "Ethereum Daily Transactions Chart." https://etherscan.io/chart/tx (accessed 10/11/2021, 2021).

[2] Ethereum.org. "Ethereum development documentation." https://ethereum.org/en/developers/docs/ (accessed 10/11/2021, 2021).

[3] A. A. Zarir, G. A. Oliva, Z. M. Jiang, and A. E. Hassan, "Developing Cost-Effective Blockchain-Powered Applications: A Case Study of the Gas Usage of Smart Contract Transactions in the Ethereum Blockchain Platform," *ACM Trans.*

Softw. Eng. Methodol., vol. 30, no. 3, p. Article 28, 2021, doi: 10.1145/3431726.

[4] Coinfyi. "ConstitutionDAO will pay more than $1.5 million in "gas fees"." https://coin.fyi/news/ethereum/constitutiondao-will-pay-more-than-1-5-million-in-gas-fees-r0gndz (accessed 10/03/2022.

[5] S. M. Werner, P. J. Pritz, and D. Perez, "Step on the Gas? A Better Approach for Recommending the Ethereum Gas Price, *Proceedings of The 2nd International Conference on Mathematical Research for Blockchain Economy (MARBLE 2020)*, pp. 161-177, 2020, doi: 10.1007/978-3-030-53356-4_10.

[6] R. Mars, A. Abid, S. Cheikhrouhou, and S. Kallel, "A Machine Learning Approach for Gas Price Prediction in Ethereum Blockchain," 2021, no. Conference Proceedings: IEEE, pp. 156-165, doi: 10.1109/COMPSAC51774.2021.00033. [Online]. Available: https://go.exlibris.link/jnNS27DK

[7] J. Garrigan, M. Crane, and M. Bezbradica, "Received Total Wideband Power Data Analysis: Multiscale wavelet analysis of RTWP data in a 3G network," presented at the Proceedings of the 22nd International ACM Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems, Miami Beach, FL, USA, 2019. [Online]. Available: https://doi.org/10.1145/3345768.3355905.

[8] Q. Sun and W. Xu, "Wavelet analysis of the co-movement and lead–lag effect among multi-markets," *Physica A: Statistical Mechanics and its Applications*, vol. 512, pp. 489-499, 2018/12/15/ 2018, doi: https://doi.org/10.1016/j.physa.2018.08.102.

[9] Q. Guo-qing, Z. Bin, and S. Xiao-qing, "Wavelet Correlation Analysis of Geodetic Signals," in *2009 Fifth International Conference on Natural Computation*, 14-16 Aug. 2009 2009, vol. 6, pp. 585-590, doi: 10.1109/ICNC.2009.322.

[10] Q. Liu, D. L. X. Fung, L. Lac, and P. Hu, "A Novel Matrix Profile-Guided Attention LSTM Model for Forecasting COVID-19 Cases in USA," (in English), *Frontiers in public health*, vol. 9, pp. 741030-741030, 2021, doi: 10.3389/fpubh.2021.741030.

[11] S. Dyllon, "Wavelet Transform for Educational Network Data Traffic Analysis," IntechOpen, 2018.

[12] J. Qiu, B. Wang, and C. Zhou, "Forecasting stock prices with long-short term memory neural network based on attention mechanism," (in English), *PloS one*, vol. 15, no. 1, pp. e0227222-e0227222, 2020, doi: 10.1371/journal.pone.0227222.

[13] A. Donmez and A. Karaivanov, "Transaction fee economics in the Ethereum blockchain," (in English), *Economic inquiry*, vol. 60, no. 1, pp. 265-292, 2022, doi: 10.1111/ecin.13025.

[14] G. A. Pierro and H. Rocha, "The Influence Factors on Ethereum Transaction Fees," in *2019 IEEE/ACM 2nd International Workshop on Emerging Trends in Software Engineering for Blockchain (WETSEB)*, 27-27 May 2019 2019, pp. 24-31, doi: 10.1109/WETSEB.2019.00010.

[15] P. J. Pritz, D. Perez, and K. K. Leung, "Fast-Fourier-Forecasting Resource Utilisation in Distributed Systems," in *2020 29th International Conference on Computer Communications and Networks (ICCCN)*, 3-6 Aug. 2020 2020, pp. 1-9, doi: 10.1109/ICCCN49398.2020.9209639.