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Neural Networks-Based Forecasting Platform for EV Battery Commodity Price Prediction

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Abstract— This study explores the impact of green energy-based economies on the growing use of electric vehicle (EV) batteries in transportation and electronic devices. Despite the environmental benefits, concerns have emerged regarding the supply, pricing, and volatility of raw materials used in battery manufacturing, exacerbated by geopolitical events such as the Russian-Ukrainian war. Given the high uncertainty surrounding EV commodity materials, this research aims to develop forecasting tools for predicting the prices of essential lithium-based EV battery commodities, including Lithium, Cobalt, Nickel, Aluminum, and Copper. The study builds on previous research on commodity price forecasting. Using Neural Networks such as LSTM that run using analytics platforms like RapidMiner, a robust and accurate models is able to be produced while require little to no programming ability. This will solve the needs to produce advanced predictions models for making decisions. As the results from the research, the models that are produced are successful in generating good prediction models, in terms of RMSE of 0,03 – 0,09 and relative errors of 4-14%.
Keywords— Analytics Platform; EV Battery Prices; Forecasting; Neural Network; RapidMiner

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I. INTRODUCTION

The growth of green energy-based economies has led to an increase in the use of batteries for cars and electronics in recent years [1] Electric vehicle (EV) batteries are preferred for their quiet operation, simplicity, and environmentally friendly nature [2]which is a positive step towards achieving carbon-neutral transportation systems. However, concerns over the supply, pricing, and volatility of raw materials used in battery manufacturing have emerged [3] The issue of volatility was highlighted during the Russian-Ukrainian war, which significantly impacted the supply and prices of battery raw materials [4] This geopolitical situation has also increased the overall risk for investors due to the volatility of this commodity [5]

As one of the asset classes with the highest uncertainty [6], we believe that predicting price is essential, particularly in the context of EV commodity materials. Previous research has been conducted to forecast the volatility and prices of commodity markets, including gold [7], oil prices [8] [9], and various metal products [10]. In this research, we will focus on creating forecasting tools for the basic commodity used in lithium-based EV battery. The main commodities used for this industry were Lithium, Cobalt, Nickel, Manganese, Aluminum and Copper. This commodity will form cathode used in the battery, such as Li-NCM, Li-NCA, and Li-FP, where graphite is used as anode [11] . With increasing demand of this commodity, reflected by sales of EV that steadily increasing from 2005 onward [12]we find urgent need to understand the pricing shift of this commodity and needs to forecast it on the future trends. Therefore in this research, we try to answer the research needs by create a models using Neural Networks algorithm, particularly LSTM. However, this whole modelling and deployment process will use Analytics platform such as RapidMiner. This approach is taken to show that the platform are able to answer the needs of predictive analytics for decision-takers, without needs to have programming ability. Further explanation of neural networks and modelling will be explained in later section.

The increasing demand for EVs subsequently leads to a growing demand for these raw materials, potentially causing notable price fluctuations in the commodity markets. Although lithium serves multiple purposes across diverse industrial and chemical sectors, its primary market in the 21st century is expected to be electric vehicles, as pointed out by [13] . Data from Benchmark Mineral Intelligence indicates that lithium carbonate prices, the most commonly traded lithium form, escalated from approximately $6,000 per ton in early 2016 to over $20,000 per ton in mid-2018 before decreasing to around $8,000 per ton in late 2019 [14]. The sharp rise in lithium prices during 2016 and 2017 can be attributed to the rapid expansion of the EV market and the increased demand for lithium-ion batteries. However, the subsequent price decline was due to an oversupply resulting from the introduction of new mines and recycling initiatives, as

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well as a deceleration in EV sales growth [15]. In [16], the researcher investigated factors impacting lithium prices, such as supply and demand, technological advancements, and government policies. The study concluded that lithium prices are influenced by all these factors, with government policies playing a particularly significant role.

Cobalt is another essential component of lithium-ion batteries, with about 60% of worldwide cobalt production utilized in battery manufacturing [17]. Cobalt prices have exhibited even greater volatility than lithium, with a substantial increase in 2017 and 2018, followed by a sharp decline in 2019. Research by [18] revealed a 110% rise in cobalt prices from January 2016 to December 2018, fueled by the rapid growth of EVs. However, the authors documented a roughly 30% price reduction from December 2018 to September 2020 due to increased cobalt supply and a slowdown in EV sales growth. Furthermore, the study suggested that cobalt prices might continue to decrease in the future as emerging battery technologies diminish the demand for cobalt. Factors such as supply chain concerns, political instability in the Democratic Republic of Congo (responsible for approximately 70% of global cobalt production), and investor speculation drove the surge in cobalt prices [19]. The subsequent price decrease resulted from new mine supplies and EV manufacturers' efforts to reduce cobalt content in their batteries [20] .Ethical and environmental concerns surrounding cobalt mining, such as child labor, human rights abuses, and environmental degradation, motivate these efforts to minimize cobalt usage in batteries [21] . Companies like Tesla are working to reduce cobalt amounts in their batteries, announcing plans to develop cobalt-free batteries in the future [22].Conversely, [23] contended that adopting sustainable mining practices and promoting human rights can mitigate the adverse social and environmental effects of cobalt mining. The authors stressed the importance of responsible mining practices that prioritize worker and local community well-being and respect their rights.

Nickel, a crucial component of lithium-ion batteries that power EVs, has experienced more stable pricing than lithium and cobalt, with a gradual price increase since mid-2019. Data from the London Metal Exchange indicates that nickel prices rose from around $12,000 per ton in mid-2019 to over $20,000 per ton in early 2021 [24] .The growing demand for nickel in EV batteries has surpassed available supplies, resulting in price fluctuations [25].Other factors include supply chain disruptions due to the COVID-19 pandemic and the impact of the invasion of Ukraine [26] . Geopolitical factors such as trade policies, resource nationalism, and environmental regulations also contribute to price volatility [27] .

Apart from lithium, cobalt, and nickel, electric vehicle (EV) batteries also utilize other metals like aluminum and copper in their production. In recent years, the prices of these metals have remained relatively steady, experiencing only minor fluctuations [28] .Nonetheless, as the growth of EV production persists, demand and supply factors influence price variations in the aluminum

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and copper markets [29] . Besides EVs, the increasing industrialization and urbanization in emerging economies contribute to a higher demand for these metals. Simultaneously, factors related to supply, such as mining output, smelting capacity, and recycling rates, play an essential role in determining prices [30].

Due to the development of deep learning, various methods employing this method, particularly using neural networks, are used to forecast characteristics of various assets. [31]as well as [32] use neural networks to forecast cryptocurrencies volatility. Three types of deep learning such as Multi-Layer Perceptron (MLP), Recurrent Neural Networks (RNN), and Convolutional Neural Networks (CNN), where most of the research use RNN-type models to forecasting [33].

This research will use RNN-type models to forecast battery-production commodity prices. RNN is a type of neural network architecture that is used to detect patterns in a sequence of data. Its main difference against feedforward networks is that it passes information in cycle, recursively. Since it has recursive information cycle, it has another weighting matrix called “hidden state to hidden state” matrix, which eventually changes how the prediction results were made [34]. Problems commonly associated with standard RNN are exploding/vanishing gradients and information storage. Hence why, the developed version of standard RNN such as LSTM and GRU has been proposed as alternative, and previous results show that LSTM and GRU has better accuracy by overcoming both issues, using effective learning [35]. [36] visualize the difference between standard RNN and LSTM Figure 1.

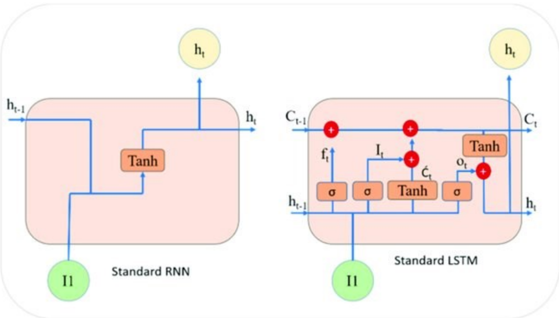

Fig 1. Difference of Standard RNN and Standard LSTM [36]

The main difference of this method is use of gate and memory cells, where this use will behave as decision maker in the network and deciding whether the data will be reserved for learning, or lost, while the memory cells record the results to the output gate. This can handle vanishing gradients issues, which eventually make model learning more effective, and create better accuracy [36].

One of the objectives of this research is not only developing a one-time use model but developing a platform to be used for forecasting. Development of analytics platform such as KNIME and RapidMiner has been a game changer in AI development in recent years by much

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simpler drag and drop interfaces rather than complete code, and has more general solutions, so it is not limited to only one sectors, even though it lacks data preparation functionality [37]

The platform predictive capability has been used in many applications, such as Chemistry [38] Healthcare and life science [39] [40] and marketing [41]. This research will contribute to creating forecasting tools that are able to give insights on the price shifts of the commodity used in EV-Battery commodities.

II. RESEARCH METHOD

The data used for this research was daily price data from January 1st, 2016 – March 23rd, 2023. The data were downloaded from investing.com, which gets the data from various metal exchanges. Then, the data will be grouped on a weekly basis, and the weekly volatility will be calculated using those data. After that, the data will be then adjusted to the price point of USD per tons, therefore the adjustment from each of the data will be done following rules in Table 1.

Table 1. Adjustment formula for the commodity prices

Commodities	Sources	Original Price Unit	Formula to adjust
Nickel (Ni)	US Futures Exchange	USD per tons	Ni x 1
Lithium Carbonate (LC)	China Futures Exchange	CNY per tons	LC x 0,15*a
Cobalt (Co)	US Futures Exchange	USD per tons	Co x 1
Copper (Cu)	US Futures Exchange	USD per lbs.	Cu x 2.20462*b x 1000
Aluminum (Al)	US Futures Exchange	USD per tons	Al x 1

**a: conversion based on CNY to USD conversion rates of 0,15 USD per 1 CNY*

**b: conversion based on 1 kg = 2,20462 lbs. and 1 ton = 1000 kgs*

Before moving on to modeling, descriptive statistics will be made to check data characteristics. Since the commodities trading were executed on business day only, where business days were defined as Monday through Friday, except where there is a holiday, then the data were treated as continuous point, regardless of the date. After that, the data will be used to create models in RapidMiner workflows. The workflow used in this research will be divided per block. The scheme is presented in Figure 2.

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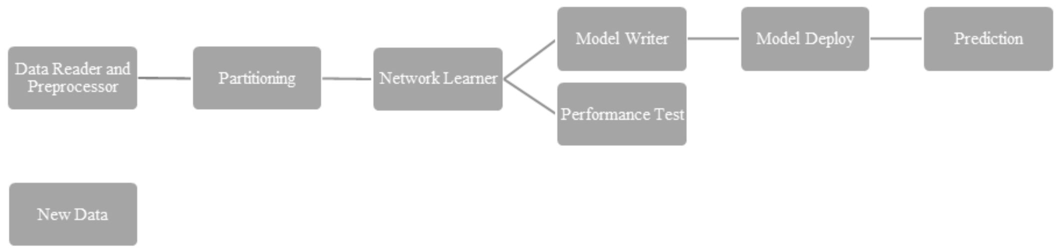

Fig 2. Schemes of Workflow Design *(author own research)*

In Figure 2, there are sequences of block in the worklfow. In each of the block, there are set of "nodes" that going to execute workflows needed for a block. Nodes are individual task that needed to execute the whole block. For example, to set up Network Learner in RapidMiner, the individual task assigned sequentially are Define Input Layers – Define LSTM Layer – Define Output Layer, where this includes with define hyperparameter for the models. In detailed, the task executed in each block are presented in Table 2.

Table 2. Block and Task of Neural Network Modelling and Deployment *(author own research)*

Block	Task
Data Reader and Preprocessor	1. Import data from repository 2. Create windows of the training and testing sets
Partitioning	1. Divide data between training and testing sets with 70:30 ratio
Network Learner	1. Define Input Layers 2. Define LSTM Layers 3. Define Output Layers
Model Writer	1. Write LSTM-based prediction models
New Data	1. Import data from repository 2. Create windows of the validation sets
Model Deployment	1. Apply model to the validation sets
Prediction	1. Create prediction on validation sets

Schema of each block in RapidMiner were as Figure 3. The first one in figure below is for the Data Reader and Preprocessing, this includes indexing portion. The top part of the figure is scheme for training data, while the bottom part of figure 3 is for deployment data.

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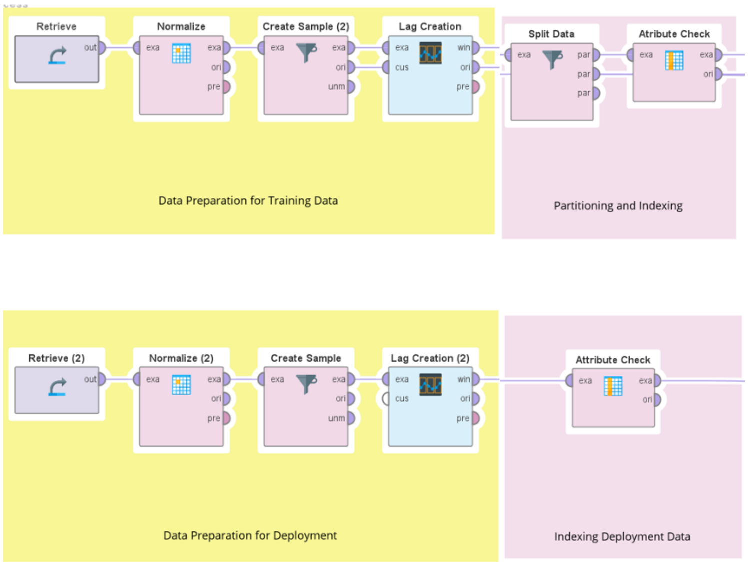

Fig 3. Data Preparation Schema for training LSTM models and data deployment (left). Indexing Schema for both data (right). *(author own research)*

The next part is schema for setting up LSTM network and hyperparameter setting, as in figure 4. In figure 4, the preprocessed data that came out from previous nodes explained in figure 3 are modelled in using nodes that contain LSTM algorithms. The model then tested using samples data and the performance of model such as MAPE, RMSE and R^2 are measured.

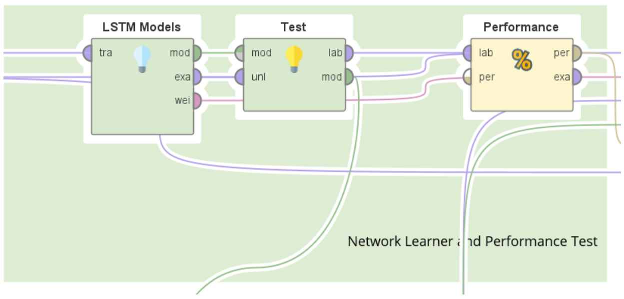

Fig 4. Network Learner Schema for training LSTM models *(author own research)*

In detail, the neural network architecture for this research is using LSTM based network, as in the Figure 5.

Fig 5. LSTM architecture for forecasting model. *(author own research)*

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In the research, the LSTM layer consist of 2 hidden layers, each with equal number of neurons, the output of this hidden layer then fed to output layer, where in this layer, the weight of the parameter will be compiled to make the finalized model. To optimize model performance and accuracy, adjustment of hyperparameter such as Activation Function, Epoch (number of iteration), and number of neurons will be needed. After the model optimization completed, the model will be deployed with new data to check its accuracy in real use. The optimization parameter we are going to use are Activation Function, which are Rectified Linear Unit (RelU) and Hyperbolic Tangent (TanH), followed with Epoch, where there will 3 epoch setting used (100,200,300) and 3 setting of neuron number (100,200,300).

Performance metrics used for the evaluation are RMSE (Root Mean Square Deviation), MAPE (Mean Absolute Percentage Error) and $R^{2.}$ RMSE are used to measure standard deviation of residuals, MAPE are used to measure absolute error of the prediction, and R^2 are used to explain variance of predicted price, based on the prediction variable used in LSTM models.

III. RESULT AND DISCUSSION

Descriptive Statistics

Table 3 consist of descriptive statistics of the commodity price from 2016 until 2023. In Table 3, we show the mean, standard deviation, and variance of the data, grouped by their year.

Table 3. Descriptive Statistics of Commodities Price from 2016 - 2023

Parameter	Nickel	Copper	Cobalt	Lithium	Aluminium	Year
N	253	252	229		253	2016
Mean	9.638	4.856	25.468		1.610	
StDev	1.042	367	2.851		81	
Variance	1.084.943	134.354	8.128.294		6.570	
N	252	251	229	160	252	2017
Mean	10.470	6.208	55.840	20.710	1.979	
StDev	1.055	499	9.216	1.988	122	
Variance	1.113.204	248.598	84.936.223	3.952.110	14.812	
N	253	254	229	240	253	2018
Mean	13.184	6.471	72.750	15.736	2.115	
StDev	1.229	457	12.980	4.740	131	
Variance	1.509.323	208.688	168.488.628	22.465.872	17.051	
N	253	265	241	242	253	2019
Mean	13.971	6.003	33.222	8.819	1.811	
StDev	1.985	258	3.807	1.353	56	

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Parameter	Nickel	Copper	Cobalt	Lithium	Aluminium	Year
Variance	3.941.652	66.529	14.495.903	1.831.054	3.105	
N	254	265	254	239	254	**2020**
Mean	13.860	6.176	31.481	5.596	1.732	
StDev	1.621	818	1.861	473	158	
Variance	2.627.423	669.119	3.463.334	224.112	24.949	
n Data	253	264	253	236	253	**2021**
Mean	18.467	9.342	51.400	17.037	2.486	
StDev	1.244	640	7.918	7.760	285	
Variance	1.547.284	409.252	62.690.161	60.216.572	81.037	
N	248	266	250	241	251	**2022**
Mean	26.024	8.830	63.623	69.806	2.711	
StDev	6.039	1.078	12.644	9.421	433	
Variance	36.469.686	1.162.649	159.876.668	88.758.025	187.615	
N	58	78	57	49	58	**2023**
Mean	26.439	8.981	40.355	56.842	2.447	
StDev	2.366	255	6.784	10.900	129	
Variance	5.596.237	64.949	46.017.934	118.799.120	16.698	

In the Table 3, we observe high spike of standard deviation and mean for the most of commodity's price, specially in 2022 and 2023. This increase is in line with the literature, and most likely cause of this increase is Russia – Ukraine war. Therefore, this spike must be handled thoroughly before modelling.

LSTM Learning Performance

All the data shown in later Table are the results of author(s) own research using Rapidminer. After we run the network with different settings explained in Section 3, the results for each of the commodities are shown in the Table 4.

Table 4. Performance Metrics of LSTM Model Optimization for Nickel Price Prediction

Activation	Epoch	Layer	MAPE	RMSE	R^2
TanH	100	100	11,20%	0,367	0,870
TanH	100	200	8,40%	0,303	0,911
TanH	100	300	12,21%	0,389	0,854
TanH	200	100	12,25%	0,397	0,847
TanH	200	200	16,90%	0,438	0,815
TanH	200	300	11,05%	0,303	0,912
TanH	300	100	8,32%	0,270	0,930
TanH	300	200	10,65%	0,314	0,905

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Activation	Epoch	Layer	MAPE	RMSE	R^2
TanH	300	300	15,54%	0,326	0,898
RelU	100	100	5,99%	0,224	0,952
RelU	100	200	5,65%	0,223	0,952
RelU	100	300	6,33%	0,222	0,952
RelU	200	100	7,77%	0,227	0,950
RelU *	200	200	5,25%	0,216	0,955
RelU	200	300	5,74%	0,220	0,953
RelU	300	100	7,06%	0,229	0,950
RelU	300	200	6,07%	0,222	0,953
RelU	300	300	5,69%	0,228	0,950

*: *model that will be used in deployment*

From Table 4, we can see that model with activation-type RelU generally perform better than TanH activation, as seen in lower RMSE and higher R^2 for each of the model. In regards of MAPE, RelU also perform better with Absolute Percentage Error of 5-8%. Another pattern that observed in the results is also Epoch and Layer affect model performance, where in this data, 200 epoch and 200 layers generally perform better rather than lower or higher epoch or layer. Therefore, we will use model with RelU activation, 200 epoch and 200 layers to be deployed. After that, we will show the performance measurement of model we create to predict Copper price in Table 5.

Table 5. Performance Metrics of LSTM Model Optimization for Copper Price Prediction

Activation	Epoch	Layer	MAPE	RMSE	R^2
TanH	100	100	6,90%	0,111	0,987
TanH	100	200	5,40%	0,082	0,993
TanH	100	300	9,97%	0,150	0,977
TanH	200	100	6,05%	0,086	0,993
TanH	200	200	5,09%	0,072	0,995
TanH	200	300	5,98%	0,087	0,992
TanH	300	100	5,41%	0,083	0,993
TanH	300	200	4,87%	0,070	0,995
TanH	300	300	9,22%	0,125	0,984
RelU	100	100	6,39%	0,093	0,991
RelU	100	200	5,77%	0,088	0,992
RelU	100	300	6,27%	0,078	0,994

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Activation	Epoch	Layer	MAPE	RMSE	R^2
RelU	200	100	4,57%	0,065	0,996
RelU *	200	200	4,46%	0,062	0,996
RelU	200	300	4,63%	0,065	0,996
RelU	300	100	4,58%	0,063	0,996
RelU	300	200	4,43%	0,062	0,996
RelU	300	300	6,94%	0,089	0,992

*: *model that will be used in deployment*

From Table 5, we also observed similar trend we got in Table 4, that is model with activation-type RelU perform better compared to TanH. Based on data in Table 5, we will use model with activation-type RelU with 200 epoch and 200 layers, because it produced model with lowest MAPE. The reason of not choosing RelU model with 300 epoch and 200 layers is because we argue that error reduction is not significant, but requires more complex model architecture. Next, we create the model for Lithium Carbonate prediction which is presented in Table 6.

Table 6. Performance Metrics of LSTM Model Optimization for Lithium Carbonate Price Prediction

Activation	Epoch	Layer	MAPE	RMSE	R^2
TanH	100	100	3,69%	0,069	0,995
TanH	100	200	7,19%	0,096	0,991
TanH	100	300	4,53%	0,085	0,993
TanH	200	100	3,64%	0,081	0,993
TanH	200	200	6,06%	0,130	0,983
TanH	200	300	5,13%	0,079	0,994
TanH	300	100	5,21%	0,064	0,996
TanH	300	200	3,56%	0,060	0,996
TanH	300	300	3,92%	0,065	0,996
RelU	100	100	1,87%	0,025	0,999
RelU	100	200	2,79%	0,040	0,998
RelU	100	300	1,17%	0,023	0,999
RelU	200	100	2,69%	0,038	0,999
RelU	200	200	5,13%	0,086	0,993
RelU	200	300	1,57%	0,021	1,000
RelU *	300	100	0,87%	0,015	1,000

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Activation	Epoch	Layer	MAPE	RMSE	R^2
RelU	300	200	1,22%	0,034	0,999
RelU	300	300	1,85%	0,037	0,999

*: *model that will be used in deployment*

From Table 6, we observed that Lithium Carbonate model with 300 epoch and 100 layers has the best performance. However, there is risk of overfitting with these models, since the MAPE were low compared to Nickel and Copper model. While lower MAPE is indicate better accuracy, when deployed, there is a risk of inaccuracy, due to model overfitting. This will cause the future prediction to be unreliable for investor decision. Regardless of that, we will proceed the deployment using these models to check its performance during deployment. Next up, we create a model to predict Cobalt Price , as presented in Table 7.

Table 7. Performance Metrics of LSTM Model Optimization for Cobalt Price Prediction

Activation	Epoch	Layer	MAPE	RMSE	R^2
TanH	100	100	5,84%	0,098	0,990
TanH	100	200	7,55%	0,087	0,992
TanH	100	300	3,50%	0,060	0,997
TanH	200	100	5,19%	0,080	0,994
TanH	200	200	3,87%	0,070	0,995
TanH	200	300	9,34%	0,108	0,988
TanH	300	100	3,54%	0,054	0,997
TanH	300	200	4,69%	0,063	0,996
TanH	300	300	4,03%	0,065	0,996
RelU	100	100	3,74%	0,058	0,997
RelU	100	200	4,86%	0,682	0,995
RelU	100	300	7,04%	0,086	0,993
RelU	200	100	5,04%	0,067	0,996
RelU	200	200	2,92%	0,051	0,997
RelU	200	300	3,50%	0,056	0,997
RelU	300	100	2,63%	0,050	0,998
RelU	300	200	6,18%	0,083	0,993
RelU *	300	300	2,35%	0,049	0,998

*: *model that will be used in deployment*

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From Table 7, we also observe similar pattern with Lithium Carbonate models which also observed for Cobalt Price prediction models in Table 6, where the model has high risk of overfitting. Regardless of that, we will proceed with model with RelU activation, 300 epoch and 300 layers to be deployed, because it has the highest accuracy compared to other model setup. To conclude the modelling phase of this research, we make the models for predicting Aluminum Price , with results presented in Table 8.

Table 8. Performance Metrics of LSTM Model Optimization for Aluminum Price Prediction

Activation	Epoch	Layer	MAPE	RMSE	R^2
TanH	100	100	5,94%	0,099	0,990
TanH	100	200	9,32%	0,150	0,977
TanH	100	300	6,52%	0,116	0,986
TanH	200	100	8,40%	0,142	0,980
TanH	200	200	6,50%	0,108	0,988
TanH	200	300	8,13%	0,155	0,976
TanH	300	100	6,64%	0,112	0,987
TanH	300	200	7,17%	0,113	0,987
TanH	300	300	7,40%	0,113	0,987
RelU *	100	100	5,53%	0,082	0,993
RelU	100	200	6,59%	0,097	0,990
RelU	100	300	10,25%	0,167	0,972
RelU	200	100	5,71%	0,088	0,992
RelU	200	200	6,37%	0,095	0,991
RelU	200	300	6,51%	0,090	0,992
RelU	300	100	6,92%	0,109	0,988
RelU	300	200	6,28%	0,098	0,990
RelU	300	300	6,15%	0,096	0,991

*: *model that will be used in deployment*

From table 8, we observe that Aluminum price prediction model is also having good performance in terms of MAPE and RMSE, and comparable with the Nickel and Copper models in Table 4 and Table 5. For deployment, we will proceed with model with RelU activation, 100 epoch and 100 layers because it has the the highest accuracy in terms of MAPE , RMSE and R^2. In summary, the model that we will use for deployment stage in our research is presented in Table 9.

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Table 9. Model used for deployment stages

Commodity Model	Activation Type	Epoch	Layers
Nickel	RelU	200	200
Copper	RelU	200	200
Lithium Carbonate	RelU	300	100
Cobalt	RelU	300	300
Aluminum	RelU	100	100

Model Deployment

Each model that has been chosen then will be deployed with new data to test its actual performance. Since the training and testing use the data from March 1st, 2023, backwards, for deployment, we will use data from March 1st, 2023, onward until March 23rd, 2023, for deployment. The results were presented in Table 10.

Table 10. Performance of deployed model using new data sets

Commodity Model	RMSE	Relative Error
Nickel	0,067	14,28%
Copper	0,061	16,62%
Lithium Carbonate	0,035	4,29%
Cobalt	0,056	10,26%
Aluminum	0.090	13,15%

From Table 10, we observe model performance is generally on par with the results from training and testing data presented in earlier table. Even though the error is bigger than the performance of original models, it's common to see that pattern. Hence why continuous learning is need for the model to stay relevant with actual condition [42]

Comparison to Previous Result

Modelling and deployment generally perform well, during learning and deployment. This show that neural network model is reliable enough to be used for price prediction. For comparison , the accuracy in terms of RMSE between model we produced with previous research are presented in Table 11.

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Table 11. Performance comparison in terms of RMSE between authors models with related research

Commodity Model	Author Research	Other Research	Sources
Nickel	0,067	0,014	[43]
Copper	0,061	0,032	[44]
Lithium Carbonate	0,035	0,014	[45]
Cobalt	0,056	-	-
Aluminum	0,090	0,212	[46]

From Table 11, we observe that our models and model from related research has comparable accuracy eventhough the authors accuracy showing higher RMSE. This higher RMSE can be optimized in upcoming research, where the improvement can include continous learning or using hybrid learning methods to optimize the accuracy. This show that analytics platform can be used as a relatively robust tools for forecasting commodities price, there is some improvement need to be done before actually using this for mass deployment. Even so, this kind of analytics platform able to provide efficient modelling with much easier use compared to traditional coding approaches.

IV. CONCLUSION

While EV-Battery shifts bring a lot of benefit in terms of pollution reduction, the commodities that drive those technology is also important part of the equations. Specially in the recent years, especially with ongoing war in the Ukraine, investor and industry need to be make more careful judgement, whether in investing or procuring the materials needed. Through this research, we conclude that neural networks-based models, that developed using available analytics platforms, which require little to no programming ability, prove to be robust enough to provide accurate, yet high versatility forecasting tools. We also conclude that LSTM using RelU activation-type is able to produce more reliable models rather than using TanH activation. Lastly, from the research we also conclude that while increasing epochs and layer might increase accuracy of the models , a proper optimization is also needed , to ensure sufficient accuracy while maintaining low computational costs.

Even so, in future research, an improvement of the models needs to be done. Not only in terms of prediction accuracy, but also in cost of computation, to make models that readily available. The other things are also while mass deployment of the model developed in analytics platform is

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possible, but there is a need for further model tuning. We also believe that other macroeconomic factors such as war, income level, political issues and others need to be included for considerations in the models. In the follow up study, we suggest inclusion of mode data sets, and parameter adjustment, especially on the optimization function might help the accuracy of the models.

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