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A novel inter-intra graph neural networks for stock price forecasting modeling cross-border relationships

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ABSTRACT

The applications of artificial intelligence for streamlining different financial services referred to as financial technology (FinTech), are now being expanded to include modernized approaches. Existing research studies mainly use machine learning (ML) or deep learning (DL) architectures, which are mainly concerned with capturing temporal relationships. Nevertheless, these methodologies ignore the fundamental relationships between stocks resulting in limited performance. Presently, Graph Neural Networks (GNN) are being used to anticipate stock prices by modeling such connections among stocks. However, they are still limited to focusing on single-stock market scenarios and disregarding the cross-market or cross-border correlations that exist among global financial systems. This constraint impairs their ability to represent the interconnectedness of various financial sectors and marketplaces. Hence, this study proposed a MEIG (Macro-Event Driven Inter-Intra Graph) model to exploit both inter-and intra-relationships among the stocks as well as modeling of intra-inter event sentiment dynamics of 42.74 million tweets and the impact of macroeconomics. The proposed model utilizes stock price correlations to assess regional interactions completely. In addition, to manage the interplay between inter and intra graphs, the Cross-Graph Attention Layer (CGAT) is also proposed to weigh the importance of stock connections within their respective intra-inter market networks. For experimentation, stock markets including SP500, SSE-50, KSE-50, BIST-100, and FTSE-100 are utilized as a pair to demonstrate differing levels of correlations such as between developed economies, superpower economies, developed to emerging economies, and emerging to emerging economies. The proposed MEIG model shows improved results in comparison with baseline methods by obtaining the lowest MSE error of 0.0009 respectively.

1. Introduction

The stock market heavily influences the economic and social infrastructure of a country (Dubey et al., 2024; Maqsood et al., 2020). The forecasting of stock prices is one of the complex challenges for investors, analysts, and academics owing to the noise, volatility, complexity, nonlinearity, and instability of stock price data (Kumbure et al., 2022). The stock market is regarded to be an open market in which different companies are permitted to raise funds for research and development, launching goods, market expansion, financial growth, and acquisitions by publicly trading their shares as well as equity securities (Kumar et al., 2021). The accurate forecasting of stock prices will be considered to be a primary baseline and foundation for investors to make informed judgments regarding trading activities (Zhao et al., 2023). In the recent past, an exponential interest of the people has been observed in the stock market (Badolia, 2016). Consequently, it is not unusual that billions of dollars of assets are being traded daily (Hoseinzade & Haratizadeh, 2019).

This indicates investors' keen interest in participating in the market with the hopes of making a profit throughout the investment period (Kumbure et al., 2022). It is one of the best platforms for trading financial instruments among traders with an approximate $83.5 trillion worldwide worth ("World Federation of Exchanges database, 2021).

Stock price forecasting accurately is a challenging research problem due to the unpredictable and volatile nature of stock prices. It is well established by the Efficient Market Hypothesis (EMH), that even though stock prices contain a lot of details and information, effective forecasting remains challenging due to its volatility (Merello et al., 2019). The

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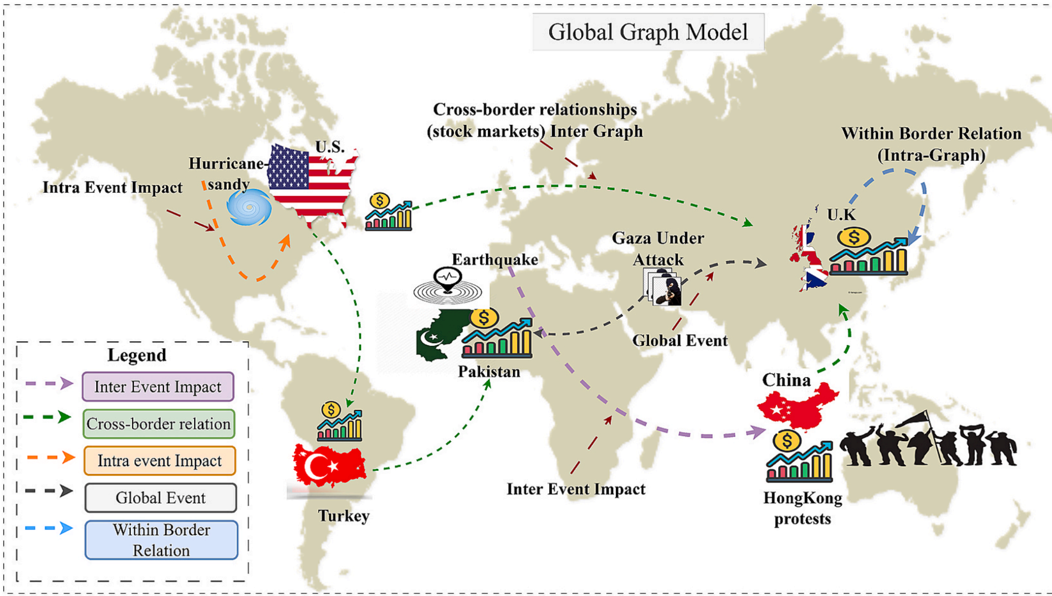

Fig. 1. Illustration of systemic dependencies in the global financial landscape of each country as graph model and their cross-border relationships, inter-events, intra-events, intra-graph (within the border), and inter-graph (cross-border).

volatility in prices of stocks arises due to several factors such as fluctuations in macroeconomic data including inflation and interest rates, geopolitical events, as well as market sentiments (Antono et al., 2019; Egbunike & Okerekeoti, 2018; Huy et al., 2021). Moreover, some other conditions include the psychological behavior of investors such as herding, emotional factors, biases, and other micro-factors (Sarwar & Afaf, 2016; Tsuchiya, 2021). The primary two main methodologies of stock price forecasting include technical as well as fundamental analysis (Agustin, 2019). The technical analysis includes autoregressive integrated moving average (ARIMA) models (Xing et al., 2405) and regression methods (Md et al., 2023) or forecasting trends by approaching the problem using classification (Ananthi & Vijayakumar, 2021; Zhao & Yang, 2023). Instead of ML and traditional methods, some deep learning models are also proposed e.g. LSTM (Long-Short Term Memory) (Zaheer et al., 2023; Qi et al., 2023; Sharaf et al., 2023). Several other combinations of techniques are also proposed to enhance forecasting including e.g. optimization techniques (Das et al., 2022; Akşehir & Kiliç, 2022; Qiu et al., 2020). At the data level, some external environment variables are also involved such as news regarding finance or social media sentiment acquired through different platforms to improve the forecasting results (Maqbool et al., 2023; Jabeen et al., 2021; Maqsood et al., 2022; Maqsood et al., 2020), etc.

However, the primary shortcoming of these studies is their lack of consideration of inter-stock relationships. More explicitly, their techniques are designed over the old deep learning paradigms e.g. LSTM, GRU, etc. (Qi et al., 2023; Zaheer et al., 2023). The objective of these methods is to anticipate future prices of stocks by making the model learn patterns from historical prices of individual stocks, thus ignoring the relationship of one stock with another while forecasting. These methods are based on the premise that stocks have no dependency relationship i.e. fluctuations in the prices of one stock do not always result in a rise or drop in the value of another stock. The methods disregard the cross-effect of stocks over time, which could persist to have an influence on stock prices (Wang et al., 2111).

Several metrics can be utilized to exploit such stock-to-stock relationships which involve exchange systems, distribution networks, stakeholder engagement, intercompany cooperation, and collective sector expertise (Chen et al., 2018; Kewei, 2002; Letizia & Lillo, 2019).

To involve these stocks' correlation-based relationships, Graph neural networks (GNNs) are one of the latest sophisticated algorithms to simulate these relationships regarding various financial instruments (Wang et al., 2111) as well as in other domains (Liu et al., 2024, 2305). In initial studies, the investigation regarding stock price association is carried out (Roll, 1988). Later on, some empirical findings of the research (Hou, 2007; Zhang et al., 2017) show the cross-impact of stocks demonstrating a specific correlation between prices (Lo & MacKinlay, 1990). Since the advancements in deep learning models, the GNN models are going to be refined to their best version by improving the graph representational learning as well as theories (Huang et al., 2407). Financial systems are complicated and necessitate a variety of data indicators as well as complex graph models, that provide substantial challenges in graph design, feature processing, and GNN modeling (Wang et al., 2111). To generate a graph that effectively models the associations among the stocks is a difficult and open research problem. The primary rationale behind this is the diversity of data as well as time-varying elements of stock prices (Wang et al., 2111). The existing studies on the graph models for finance extensively designed the GNN for the prediction of stock trends instead of price prediction. In addition, several measures are investigated to connect stocks in the graph, for instance, sector-based relationships, the prominence of every single stock in news headlines, or simply any other metric (Chen et al., 2018; Patil et al., 2020). Nevertheless, studying more accurate criteria among stocks is a continuously investigated topic. For example, previous studies neglected the relationships between local stock markets and global markets, as well as the relationships between macroeconomic factors and stock markets in the context of graph models. Moreover, the existing graph models focus on solely intra-stock markets to build relationships for stock price forecasting thus disregarding the inter-stock market relationships among stocks. Fig. 1 shows the pictorial representation of a partially globally interconnected financial system.

Globalization has made financial markets more connected since changes in one nation's economy or policies can have an impact on stock values in other regions (Shahzad et al., 2022). For instance, some mega-events such as political or other financial crises in one country e.g. U.S., also have an impact on the stock prices of another country e.g. Pakistan. Likewise, good economic statistics from China can affect the markets of developing nations such as Turkey or Pakistan. These connections among stocks are mostly complicated because they are influenced by both macroeconomic (such as inflation, interest rates, and trade policies) and geopolitical (such as political, terrorist, cultural, and natural

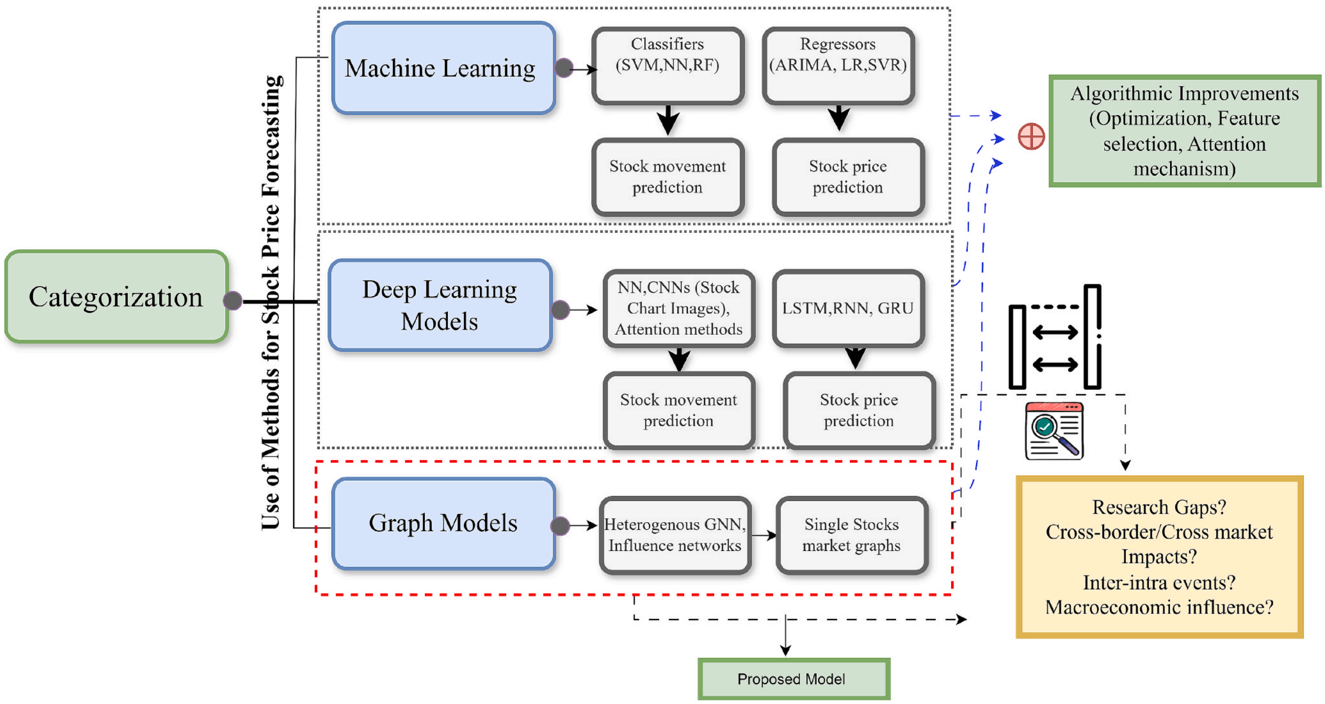

Fig. 2. Visual Summary of existing research studies on stock price forecasting.

disaster events) variables at both intra-and inter-level. Similarly, the event of COVID-19 strongly affected China at the initial level, which ultimately led to a decline in stock prices because of lockdown situations. Since China is a significant participant in international supply chains, interruptions in trade and production have a rapid impact on foreign markets (Gao et al., 2022). The negative news sentiments from one country may trigger significant selloffs in various markets because of concerns about a worldwide recession. Hence, to guide investors about more optimum risk management and investment plans, the cascading effects possess greater importance to study how different events in one region propagate to affect the stock prices in other regions. To model such cross-market or cross-border impacts in addition to intra-market, a MEIG (Macro-Event Driven Inter-Intra Graph) model is proposed in this study to exploit both inter (cross-border)-and intra-relationships (within-border) among the stocks of different financial markets as well as modeling of intra-inter event sentiment dynamics. The MEIG model considers the stock markets as intra-graph in addition to building their inter-graph by modeling the cross-country stock markets. These inter-intra graphs are processed by Graph neural networks in addition to inter-intra event sentiment and macroeconomic as nodes features. Moreover, the Cross-Graph Attention Layer (CGAT) is also proposed to weigh the importance of stock connection within their respective intra-market and inter-market networks. This emphasizes the importance of inter-connection over intra-connections between stock markets to be utilized for the forecasting of stock prices. Different stock markets, including the SP500 (United States), SSE50 (China), KSE-50 (Pakistan), BIST (Turkey), and FTSE (United Kingdom), have been used in pairs to conduct experiments to show varying degrees of spill-over effects, including intermarket correlations and their influence on stock price predictions. In the context of inter-intra events, several tweets regarding events have been collected to carry out event sentiment. The proposed MEIG model outperforms intra-stock market correlations in terms of forecasting. The following are the contributions of this research study:

- A MEIG model is proposed to model inter-intra relationships among stock markets to carry out more optimum stock price forecasting.
- The impact of intra-inter event sentiments as well as macroeconomic dynamics on both intra-inter graph models is also exploited to build a more complete interconnected system of financial components for forecasting.
- Cross-Graph Attention Layer (CGAT) is also proposed to rate the significance of the inclusion and importance of inter and intra-network during forecasting.
- Different levels of cross-border correlations have been studied among economies such as between developed economies, super-power economies, developed to emerging economies, and emerging to emerging economies.

The rest of the paper is organized as follows; Section 2 presents the Related work covering the extensive literature on stock price forecasting, section 3 describes the proposed work, section 4 shows experimental results with discussion, section 5 provides implications of the study, and in last section 6 provides the conclusion followed by future research directions.

2. Related work

A detailed literature review of the existing methods of stock price forecasting is discussed in this section. More precisely, prior methods are divided into traditional and machine learning techniques. Some advanced methods include the use of deep learning models, and in the latest studies, some sophisticated algorithms including GNN models have been studied (Zhang et al., 2024). The research gaps and limitations for every kind of approach are also highlighted in connection to the research proposed in this paper. A pictorial representation is depicted in Fig. 2.

2.1. Machine learning for stock forecasting

One of the most popular and extensively applied approaches to stock price forecasting which are employed in existing studies is the machine learning algorithms (Nikou et al., 2019). Stock price forecasting is a complicated research problem due to the fluctuating nature of stock prices caused by environmental variables such as business economic development, macroeconomic variables, financial information, media news, and the public's perception (Daradkeh, 2022). Some traditional approaches that are utilized in previous studies include linear regression (LR), and support vector regression (SVR) trained using the input of stock prices historical records (Dash et al., 2023; Emioma & Edeki, 2021; Sangeetha & Alfia, 2024). Instead of utilizing the baseline algorithms, modification and improvement have also been introduced. Such as SVR models are improved by involving the concept of primal cost function and optimizing the parameters of the SVR (Wang et al., 2023). This improvement in the original SVR model is called BA-SVR which shows superior results in comparison with the SVR model designed with polynomial and sigmoid kernels. To capture more information from stock prices such as linear and non-linear, some hybrid algorithms were also proposed such as combining the benefits of the SVR and ARIMA models into one standalone model (Su, 2021). It is indicated in their findings that individuals perform poorly in comparison with their fused version. Following on, instead of tackling the problem using a regression algorithm for explicit price prediction, some classification models were also employed to solve the stock price prediction problem as trend prediction. These methodologies employ several classification models including random forest (RF), KNN, Naïve Bayes, and Support Vector Machines (Kumar et al., 2018; Pagliaro, 2023). These algorithms were designed to predict the trend of future prices as either "upward" or "downward". To improve this stock trend prediction problem, some fusion methods involving SVM and fuzzy theory sets were also proposed (Hao et al., 2021). Subsequently, some techniques have performed the fundamental analysis of stock returns to guide investor decisions about their shares. This fundamental analysis included the analysis of different ratios such as earnings to price ratio (EPS), and extraction of information from financial reports, e.g., income statements and balance sheets (Hao et al., 2021). Although all these approaches show good results, however still there is a research gap to improve the models since stock patterns are highly volatile, and sequential and are heavily influenced by feature engineering techniques (Yuan et al., 2020). Secondly, these, methods lacked the ability to consider the stock-to-stock relationships while forecasting the prices of particular stocks e.g. corporation relationships among stocks (Chen et al., 2018).

2.2. Deep learning for stock forecasting

In comparison with traditional ML methods, deep learning techniques are the more advanced, sophisticated, and latest methods. Besides its breakthrough in other applications (Bukhari et al., 2023, 2022, 2023), these techniques have been significantly employed in the finance domain e.g. for the problem of stock price prediction and demonstrate excellent results (Qiu et al., 2020; Shah et al., 2021; Zhao et al., 2021). In the context of deep learning, Recurrent Neural Networks (RNN), and their enhanced models such as LSTM and GRU are the most widely used (Zhao et al., 2021). One of the LSTM variants called BiLSTM was employed in (Shah et al., 2021) to make the model learn the information from past prices to forecast future prices. To improve their performance, a complementary module was also added e.g. attention mechanism to make the model focused on the most important previous time steps to forecast future prices (Qiu et al., 2020). Compared to the unidirectional techniques, the investigators established a basis for greater depth and learning. Hence, to enhance the feature learning, tweets were first extracted from Twitter and later on, sentiments were extracted from these tweets to include as a feature for stock price forecasting (Jabeen et al., 2021). This sentiment was computed against different events such as COVID (Jabeen et al., 2021), and Brexit Event sentiment (Maqsood et al., 2022) to study the impact of the least and major contributing countries. Likewise, some studies amalgamated different types of representation of stock prices such as including both candlestick stock-chart images and historical records (Kim & Kim, 2019; Lin et al., 2021). In (Kim & Kim, 2019; Lin et al., 2021), separate branches in the deep learning model were added to process different kinds of information such as LSTM to process historical time series data, while the CNN models was designed to extract information from stock-chart images. Their proposed algorithm achieved good results due to the combination of two data representations when compared with individual models. The outcomes of their study also suggested that, with respect to images, candlestick chart depiction of stock prices represents one of the most promising indications for a model for stock price prediction. In (Kanwal et al., 2022), another hybrid model was designed namely the Bidirectional Cuda Deep Neural Network LSTM (BiCuDNNLSTM) together with a one-1D Convolutional Neural Network (CNN) for stock price anticipation. The results show that their proposed hybrid model performed well at accurately anticipating stock prices and was reliable at advising investors to make sound choices. To put it simply, the DL outcomes were superior but simple deep learning models such as LSTM, etc., disregard the associations among stocks while forecasting the prices of particular stocks.

2.3. Advanced deep learning-graph models for stock forecasting

In the recent past, more advanced variants of neural networks namely graph neural networks were designed to work with graph-structured data to empower graph learning (Liu & Zhou, 2022). The intuition behind graph learning was the idea from convolutional neural networks in which the working of convolution operation has been adapted. This customized convolution was combined with standard neural networks, hence called graph neural networks (GNN) (Kipf & Welling, 2016). The input data of GNNs was a graph model in which attributes of the particular problem were provided on every node of a graph. This kind of configuration made the model learn important features from each node by summing up the associations from neighboring nodes. In the last, the function of transformation was operated on the data linearly. Moreover, these beneficial qualities of the GNN model increase its usage in various graph-assisted application scenarios, particularly financial applications. In the existing literature, for instance, in (Chen et al., 2018), a graph has been constructed symbolizing stocks on nodes and edges among nodes was proposed using the shareholding information. Nevertheless, the underlying graphs were incapable of presenting and reflecting the intricate relationships among stocks, because of the minimal cross-shareholding of stocks. Subsequently, the fusion of the two models namely GNN and GRU was designed to predict stock movements by framing the problem as a classification task (Ye et al., 2021). The experiments of their research were validated on two Chinese stock indexes, and the findings proved the worth of their method in comparison with traditional methods. Likewise, in (Xiang et al., 2022), an enhanced version of the GNN model referred to as heterogenous GNN was proposed to anticipate future prices. During training, their model itself starts learning the complex relationships between stocks. More precisely, the U.S. and China were the two stock markets on which simulations were carried out to draw the findings. The outcomes of their model show superiority over the baseline methods. Similarly, GCNET was another enhanced GNN model (Jafari & Haratizadeh, 2022). The very initial step of their proposed framework was to first build the influence network with a primary rationale to build edges among stocks. In the next step, different prediction algorithms were designed to initialize the target value of nodes. Their model was designed to predict stock movements instead of explicit price prediction. To improve efficacy, the attention module was incorporated in (Kim et al., 2019), while the graph was formed by reliance on data from the Wiki repository. Some extra environmental variables such as social media information were also included in the graph models (Sawhney et al., 2020). Existing studies have shown that GCN algorithms were primarily used for stock price prediction problems, with every node showing stocks in the graph containing only historical features; nevertheless, unlike previous studies, this study introduces an entirely novel idea wherein nodes were viewed as multi-variate time series using

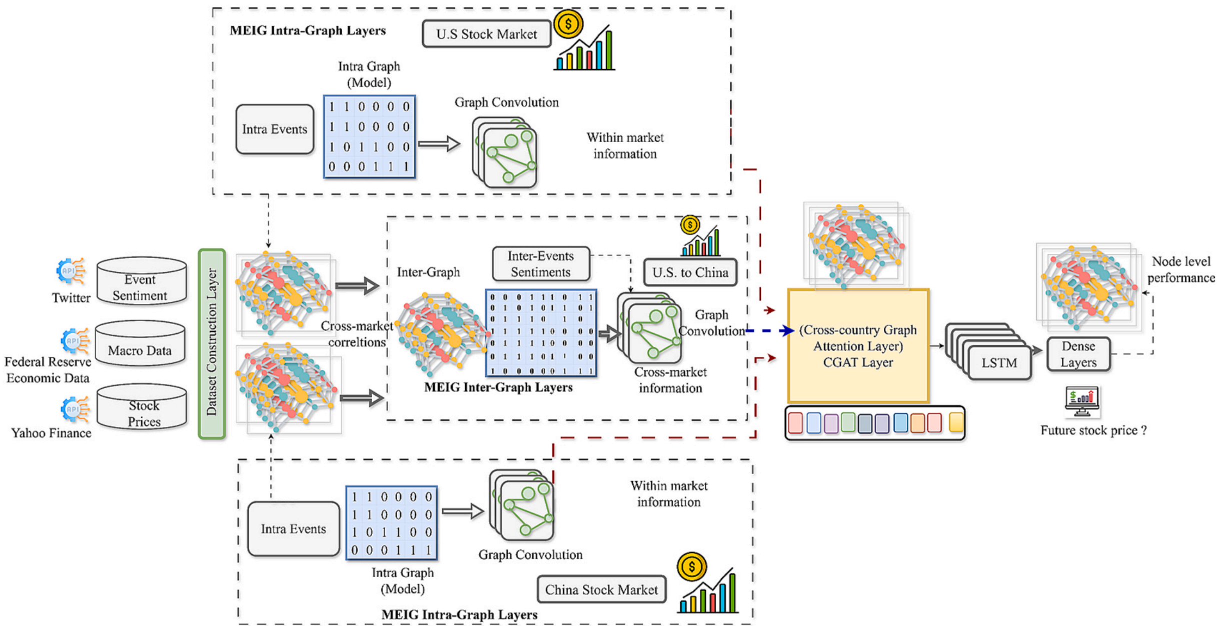

Fig. 3. A visual representation of the proposed MEIG model (Macro-Event Driven Inter-Intra Graph).

macroeconomic data and event sentiment. Second, existing studies do not account for the relationships between stock markets.

3. Proposed methodology

In this section, a detailed explanation of the proposed model MEIG called a Macro-Event Driven Inter-Intra Graph is presented. The proposed MEIG model first builds intra-graphs of different stock markets and in the next step, intra-graph networks are combined to generate an inter-graph. This inter-graph captures the cross-country interdependencies since most of the studies remain limited to single-country markets. Furthermore, the model's predictive potential is enhanced by using country-specific macroeconomic indicators which include GDP, inflation, interest rates, CPI, and unemployment rates as node features. The dynamics of event sentiments at both inter and intra levels are also employed within the network of graph models to improve stock price forecasting. Fig. 3 depicts a graphical representation of the proposed framework MEIG with detailed steps provided below:

3.1. Background and preliminaries

In the latest research to improve stock price forecasting models, the idea of standard neural networks is extended to model the stock correlations by adapting to graph-structured data. One of the main constituents of graph neural networks is the inclusion of graph convolutions which are adapted from the convolution of CNN (Convolutional neural networks) models. In the finance domain, several use cases of GNN models are implemented (Wang et al., 2111). One of the most important is to predict future trends in stock prices by framing the problem as a classification task (Ye et al., 2021). Similarly, the second way is based on anticipating the stock's precise future price, and this is a more complex procedure than predicting stock movement. Consequently, an enormous quantity of research studies focused on predicting stock movements rather than market prices. The major limitation in existing studies in which GNN models are employed for stock price forecasting is their ignorance of the impact of cross-country relationships and global economic factors. Nevertheless, in today's integrated financial system, events or macroeconomic conditions in one market can significantly impact other countries' stock markets which are not considered in existing models. In the context of these challenges, there is a need to design a more complete model that not only considers relationships among stocks at a local stock market level but also considers the relationships with stocks across the country (i.e. global stock market level). Additionally, these interdependencies as well as macroeconomic factors and local-level country-specific event sentiments improve the accuracy and robustness of stock price forecasts.

In the proposed MEIG framework, the objective is to construct a model that forecasts future stock prices by utilizing both inter-intra-stock relationships within and across countries, macroeconomic factors, as well as sentiment dynamics of inter-intra events. More precisely, conventional and fundamental time series forecasting involves the historical stock price data, and the objective is to predict the future price of a particular stock s at day t denoted as y^s_d. The univariate time series forecasting is represented as:

$$y^s_d = f[x^s{}_t] = f[x^s{}_{d-P}, x^s{}_{d-P+1} \cdots\cdots . x^s{}_{d-1}] \tag{1}$$

In the above Eq. (1), y^s_d is the future stock price of a particular stock s at time d, while the $x^s{}_t$ is the current stock price and the P symbolizes the lag size or window size. This type of formulation only implies past price trends while ignoring other crucial factors that influence stock price shifts. For example, in this study, the univariate time series has been transformed into a time series with multiple variables by incorporating inter-intra event sentiments and macroeconomic country-specific data as node features of the graph. Mathematically, on an intra-graph (e.g. stocks of SP500 stock market), the inter-intra-event sentiment i.e. $sentiment_t$, macroeconomic indicators $Macro_t$, and daily historical price data x_t of stock s are modeled as multi-variate time series on the nodes of a graph as shown below:

$$\begin{aligned} y_d{}^s &= f\left[x^s{}_t, Macro_t, Intra/InterEvent_t\right] \\ &= f\left[x^s{}_{d-P}, Macro_{d-P}, Intra/InterEvent_{d-P}\right] \cdots\cdots . \left[x^s{}_{d-1}, Macro_{d-1}, \right. \\ &\quad \left. Intra/InterEvent_{d-1}\right] \end{aligned} \tag{2}$$

In the above Eq. (2), $Macro_t$ is a macroeconomic indicator at time step $\boldsymbol{t}$, and $\boldsymbol{x^s}_t$ shows the closing price of stock $\boldsymbol{s}$ at time step $\boldsymbol{t}$ and lastly, the $Intra/InterEvent$ denotes the event sentiment and belongs to various kinds of events that happen at the inter and intra level, and has values that are shared by all stocks. The more comprehensive form of the equation for intra-graph is given below:

Table 1
List of symbols and their meaning.

Symbols	Meanings
y_d^s	Future stock price on day d for stock s
$x^s{}_t$	Current day stock price
$E = \{e_1, e_2, e_3, \cdots\cdots.e_n\}$	Set of edges
$Macro_t$	Macroeconomic indicators at time t
$s\ tocks = \{s_1, s_2, s_3, \cdots\cdots.s_n\}$	Set of stocks
C_i	Specific country stock market
$G_{intra} = (V_i, E_i)$	Intra-graph model
$G_{inter} = (V_i, E_i)$	Inter-graph model
U	Graph Fourier
α	Set of attention weights for graphs
θ_{inter}	Correlation threshold for inter-graph construction
Z	Output of the graph convolution
P	Lag size in time series
$\mathbb{R}^K$	Vector of polynomial coefficients
$E_{inter} \cup E_{intra}$	Union of intra-markets with inter-markets
$v_j^{C_i} \in V_i$	Stock of country C_i in inter-graph
v_k^m	Node of graph for country m

$$y_d{}^s = f\begin{bmatrix} (x^s{}_{d-P}, \cdots\cdots.x^s{}_{d-1}), \\ (Macro_{d-P}, \cdots\cdots.Macro^s{}_{d-1}), \\ (Inter - Intra\,Event^k{}_{d-P}, \cdots\cdots.Inter - Intra\,Event^k{}_{d-1}) \end{bmatrix} \tag{3}$$

In the above Eq. (3), $\boldsymbol{k}$ represent the event sentiment, for instance, for the U.S. stock market i.e. S&P500, the intra-event sentiment is “U.S. election” while the inter-event sentiment is “Hong Kong protests”. However, this intra-graph disregards the international connections among markets and regards them as distinct entities. The suggested MEIG model closes this gap by explicitly demonstrating cross-country interactions, resulting in a more complete structure for financial forecasts. Table 1 shows the symbols employed in this study and their corresponding meanings.

3.2. Proposed MEIG framework

To reflect the intricate interactions between stocks, the stock market is modeled as a graph-based system with nodes representing stocks and edges representing connections including price correlations, and stock price reactions to macroeconomic indicators such as stock returns during periods of high inflation. Mathematically, suppose a graph G composed up of various nodes N and edges E that connect nodes. These nodes N are also referred to as vertices of a graph denoted as V. If a graph comprises of n nodes and each symbolizing a set of stocks i.e. $s\ tocks = \{s_1, s_2, s_3, \cdots\cdots.s_n\}$ and their set of corresponding edges $E = \{e_1, e_2, e_3, \cdots\cdots.e_n\}$, the connection between two stocks s_i and s_j in a graph is indicated by $e_{i,j}$ where $i \neq j$. Following are the detailed components of the MEIG model:

3.2.1. MEIG-GNN – Intra graphs

To build an intra-graph in the MEIG model, each country or stock market C_i has its own stock market intra-graph represented as $G_{intra} = (V_i, E_i)$ in which $V_i = \left\{v_1^{C_i}, v_2^{C_i}, v_3^{C_i}, \cdots\cdots.v_4^{C_i}\right\}$ is a collection of stocks symbolized on nodes of intra-graph G_{intra} of particular country C_i. In addition, the set of edges among the stocks to portray their relationships based on price correlations are denoted as $E_i \sqsubseteq V_i \times V_i$. Different types of data are encapsulated in a node $v_j^{C_i} \in V_i$ of the intra-graph of the market C_i as feature vectors on a particular time t denoted as $f_{v_j^{C_i}}(t)$ as shown below:

$$f_{v_j^{C_i}}(t) = \Big\{GDP_{C_i}(t), UNRate_{C_i}(t), Inflationrate_{C_i}(t), Interestrate_{C_i}(t), CPI_{C_i}(t)\Big\} \bigcup \{IntraSentiment^k(t)\} \bigcup \{x^s(t)\} \tag{4}$$

In the above Eq. (4), $GDP_{C_i}(t)$ denotes the GDP of a particular country C_i at time t, likewise, $UNRate_{C_i}(t), Inflationrate_{C_i}(t), Interestrate_{C_i}(t)$, and $CPI_{C_i}(t)$ shows the unemployment rates, inflation rates, interest rates, and Consumer price index (CPI) of a particular country C_i at time t. Similarly, $Intra{-}sentiment^k$ is the sentiment of a particular event k in an intra-graph G_i while x^s is the closing price at time t. All these local graphs are denoted as $G = G_{intra_n}$ capturing each stock market of a particular country C_i (i.e. nodes $v_j^{C_i} \in V_i$ symbolizing $\{Macro_t, Intra/Inter - Sentiment_t, x_t\}$ vector of stock v_j) and are fused to build a global graph to capture cross-market relationships among stocks.

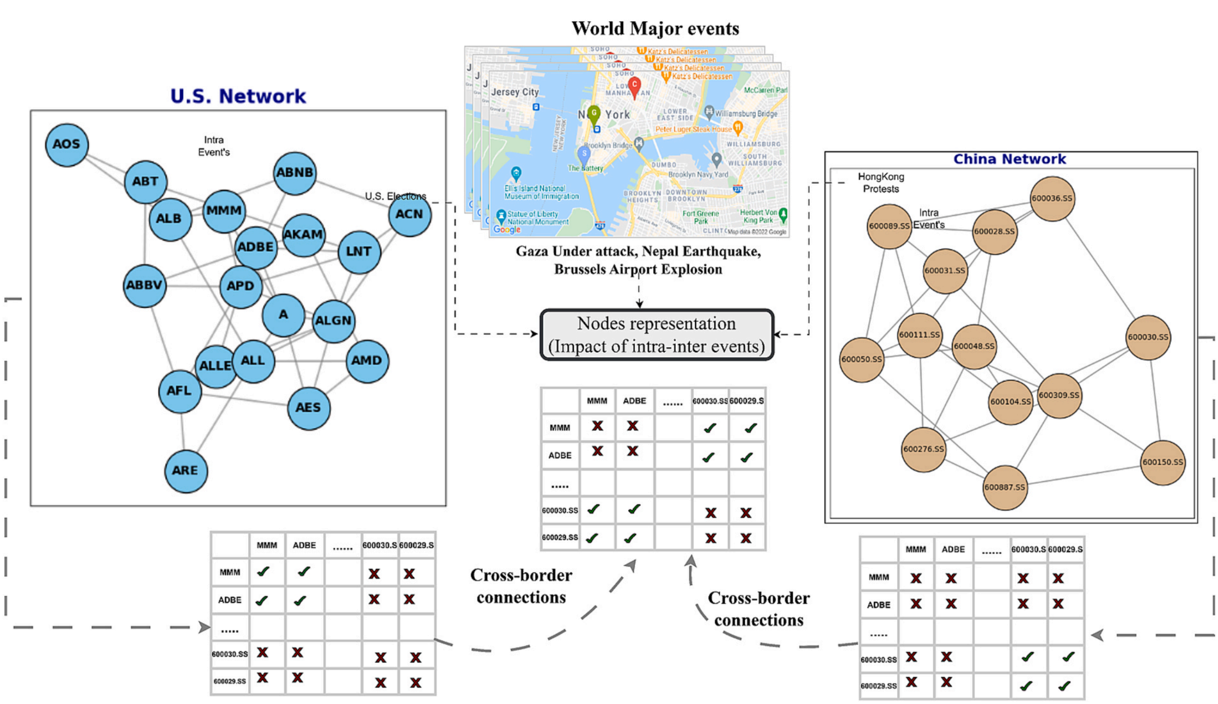

Fig. 4. Modeling of inter-intra relationships among stock markets of different countries in MEIG model – Dual Graph layers Branches in MEIG.

Table 2
Summary of Macroeconomic indicators collected for each country and their source.

Indicator	Country	API Symbol
Gross Domestic Product	U.S.	GDP
Unemployment rate	U.S.	UNRATE
Inflation, consumer prices in the United States	U.S.	FPCPITOTLZGUSA
Interest Rates, Discount Rate for United States	U.S.	INTDSRUSM193N
Gross Domestic Product for China	China	MKTGDPCNA646NWDB
Youth Unemployment Rate in China	China	SLUEM1524ZSCHN
Inflation, consumer prices in China	China	FPCPITOTLZGCHN
Interest Rates, Discount Rate for China	China	INTDSRCNM193N
Gross Domestic Product for United Kingdom	U.K.	UKNGDP
Inflation, consumer prices in the United Kingdom	U.K.	FPCPITOTLZGGBR
Interest Rates, Discount Rate for United Kingdom	U.K.	INTDSRGBM193N
Unemployment Rate in the United Kingdom	U.K.	AURUKM
Gross Domestic Product for Pakistan	PK	MKTGDPPKA646NWDB
Inflation, consumer prices in Pakistan	PK	FPCPITOTLZGPAK
Liquid Liabilities to GDP for Pakistan	PK	DDDI05PKA156NWDB
Youth Unemployment Rate for Pakistan	PK	SLUEM1524ZSPAK
Gross Domestic Product for Turkey	Turkey	MKTGDPTRA646NWDB
Inflation, consumer prices for Turkey	Turkey	FPCPITOTLZGTUR
Interest Rates, Discount Rate for Turkey	Turkey	INTDSRTRM193N
Infra-Annual Labor Statistics: Unemployment Rate Total: From 15 to 64 Years for Türkiye	Turkey	LRUN64TTTRQ156S

3.2.2. MEIG-GNN – inter graph

The inter-GNN model builds the global graph by combining the intra-graphs portraying each stock market. Consider an inter-graph $G_{inter} = (V_{i,}E_i)$ in which $V_i = \left\{v_1^{C_{i_1}}, v_2^{C_{i_2}}, v_3^{C_{i_3}}, \ldots\ldots v_4^{C_{i_n}}\right\}$ is a collection of stocks symbolized on nodes of an inter-graph G_{inter}. The nodes of the global graph are defined as:

$$Inter_V = \bigcup_{i=1}^{n} V_i, E_{total}, where E_{total} = E_{inter} \cup E_{intra} \tag{5}$$

In the above Eq. (5), V_i shows the collection of all stocks belonging to a specific country's market C_i. Every stock denoted as $v_j^{C_i}$ from G_{intra_n} is a part of $Inter_V$. The edges in G_{inter} is employed to create relations among the stocks belonging to different countries. This can be mathematically formulated in Eq. (6):

$$E = \left\{ \left(v_j^{C_i}, v_k^{C_m} | i \neq m, and corr\left(v_j^{C_i}, v_k^{C_m} > \theta_{inter} \right) \right\} \tag{6}$$

In the above Eq. (6), $(v_j^{C_i}, v_k^{C_m})$ is an edge to connect two stocks belonging to different countries denoted as C_i and C_m i.e. v_k^m from stock market C_m and v_k^i from stock market C_i while *corr* denotes the correlation measure between two stocks depending upon stock prices. The symbol θ is a threshold value used to assess the importance of an association. If the correlation reaches this value, an edge is formed among the nodes in the global network. The general representation of inter-graph is defined as:

Table 3
Dataset details and corresponding intra-inter events.

Stock Index	Markets	Intra-Event
KSE-100	Karachi Stock Exchange (Pakistan Stock Exchange – PSX)	Lahore Blast 2016
FTSE-100	Financial Times Stock Exchange 100 Index (London Stock Exchange – LSE, United Kingdom)	Scottish independence referendum 2014
SP500	Standard & Poor's 500 Index (New York Stock Exchange and NASDAQ – USA)	US Election2012
SSE50	Shanghai Stock Exchange 50 Index (Shanghai Stock Exchange – SSE, China)	HongKong Protest (2014)
BIST-100	Borsa Istanbul 100 Index (Borsa Istanbul – Turkey)	Cyprus Hijacked Plane 2016

Table 4
Collected tweet counts for intra-inter events.

Intra Events	Total Tweets	Inter Events	Total Tweets
Scottish independence referendum 2014	1,524,166	Brussels Airport Explosion 2016	5,869,990
US Election 2012	1,740,258	Hurricane Sandy 2012	14,914,566
Hong Kong Protest 2014	1,188,372	Gaza Under Attack 2014	2,886,322
Lahore Blast 2016	1,149,253	Irish General Elections 2016	758,803
Cyprus Hijacked Plane 2016	702,586	Nepal Earthquake 2015	12,004,187

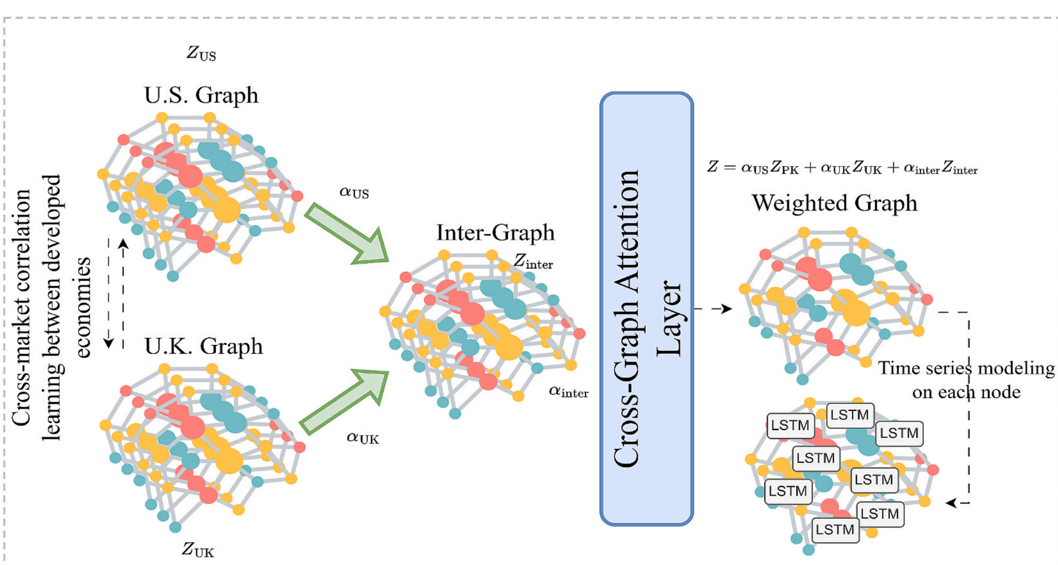

Fig. 5. A pictorial representation of the proposed CGAT Layer in the MEIG Model.

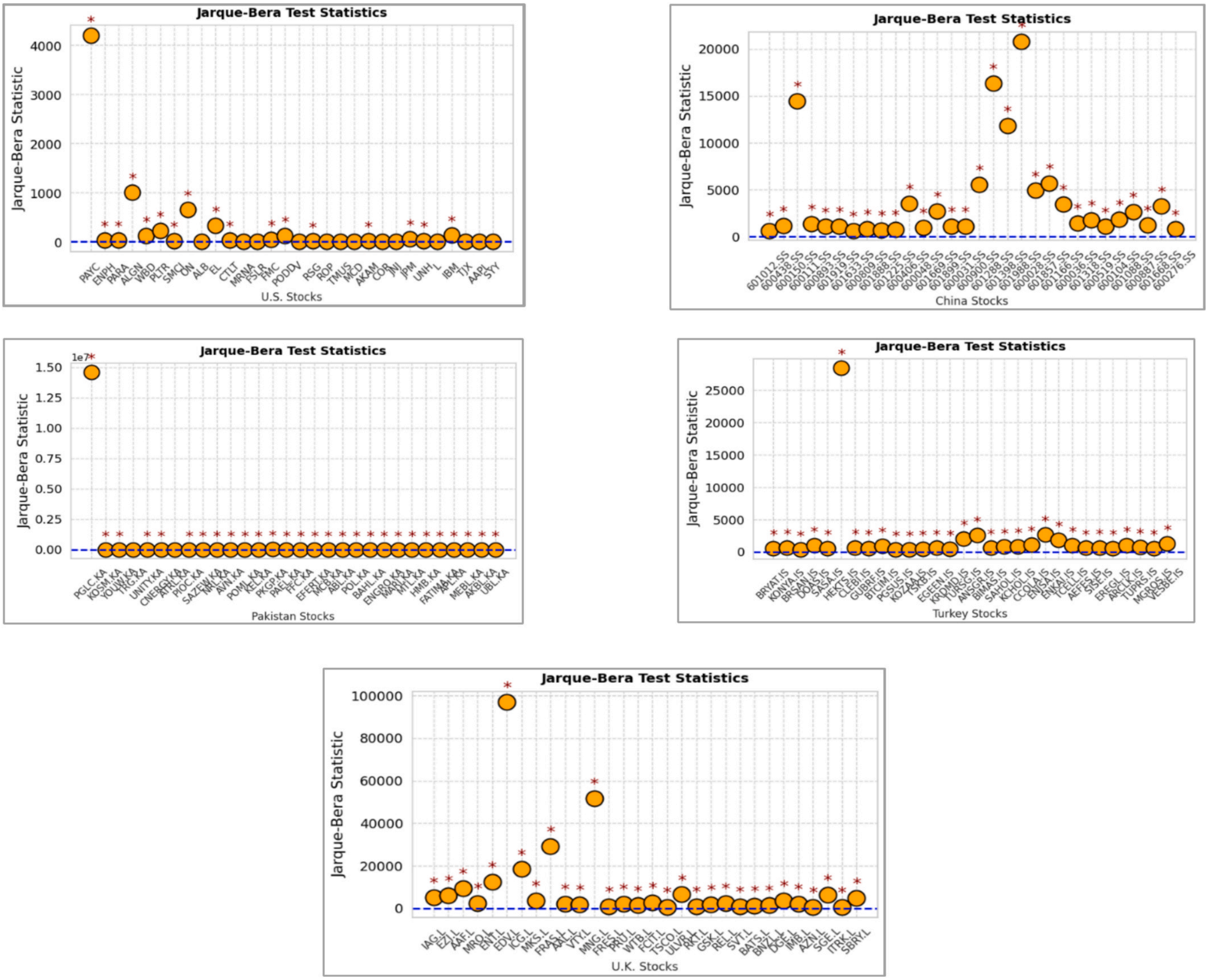

Fig. 6. Statistical analysis of the top 15 and last 15 volatile stocks of all five stock markets including p-value and Jerque-Bera statistic.

Table 5
Results of the MEIG model by modeling cross-market economies (U.S. and U.K.) with intra-events “US Elections” and “Scottish independence referendum” and inter-event “Gaza Under Attack“ and “Lahore Blast”.

Exp#	MAE	MSE	RMSE	Macro	Inter Events	Intra Events	Inter/Intra Events	Forecast Horizon
1	0.01094	0.00024	0.01546	×	√	×	×	1
2	0.01115	0.00024	0.1563	×	×	√	×	1
3	0.1156	0.00026	0.01615	×	×	×	√	1
4	0.0111	0.00024	0.0156	GDP	×	×	√	1
5	0.01146	0.00025	0.01595	GDP	×	×	×	1
6	0.01619	0.00046	0.02145	Inflation	×	×	√	1
7	0.01189	0.00027	0.01632	Inflation	×	×	×	1
8	0.01092	0.00024	0.01539	Interest	×	×	√	1
9	0.01115	0.00024	0.01557	Interest	×	×	×	1
10	0.01129	0.00025	0.0158	UNRATE	×	×	√	1
11	0.01136	0.00025	0.01594	UNRATE	×	×	×	1

$$G_{inter} = \left(\bigcup_{i=1}^{n} V_i, \left\{ v_j^{C_i}, v_k^{C_m} \middle| \neq m, and corr\left(v_j^{C_i}, v_k^{C_m} > \theta \right) \right\} \right) \tag{7}$$

This approach effectively represents the interconnectivity of stocks between various stock markets in various countries, taking advantage of the connections established by stock returns correlation and macro-economic factors. The modeling of inter-intra relationships among stock markets is visually depicted in Fig. 4.

3.3. Node representation of MEIG-GNN

The nodes representation of MEIG-GNN models includes the multi-variate times series data of stocks at the intra-level as well as inter-level. Each stock symbolized as a node contains historical stock prices,

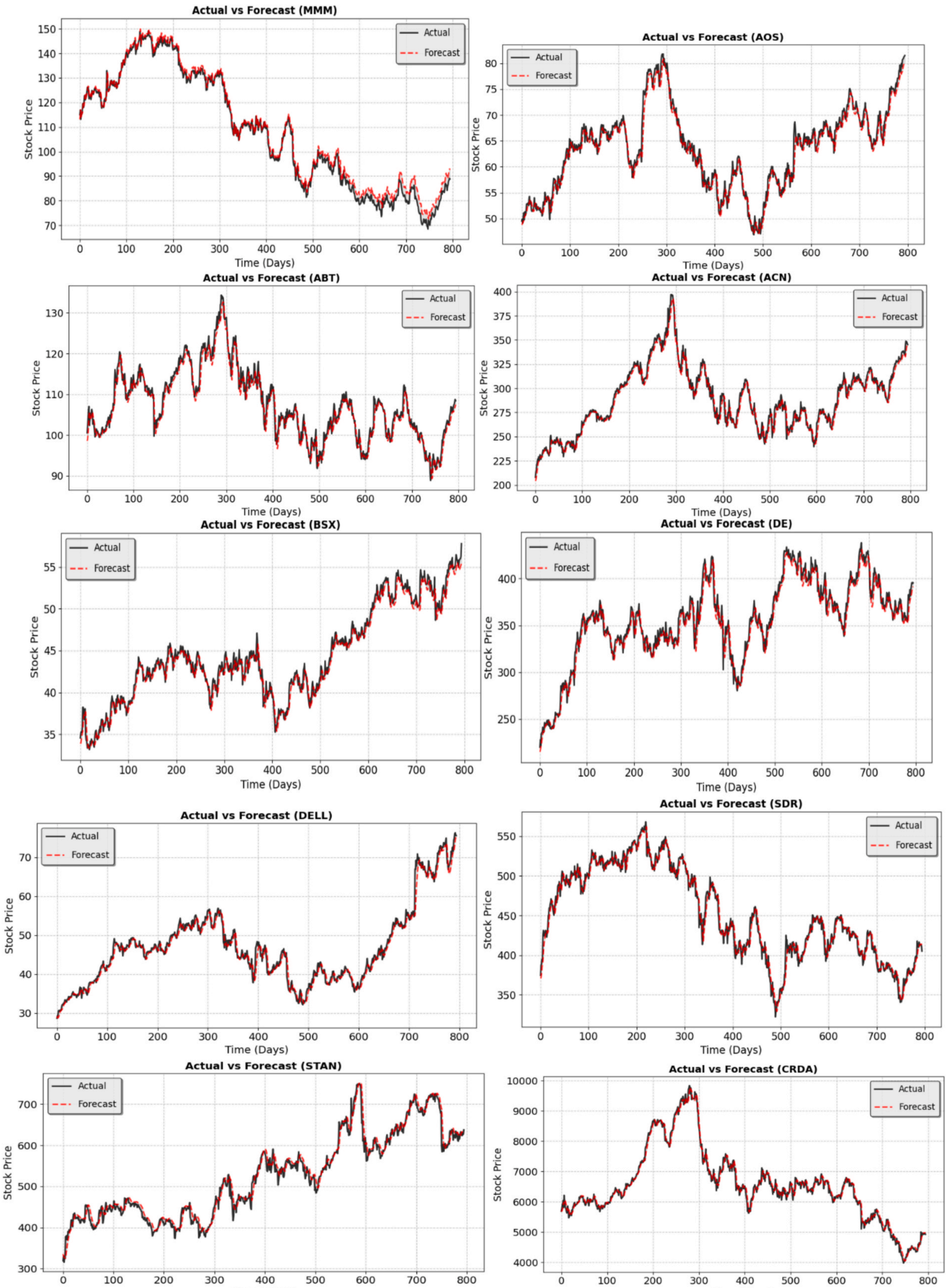

Fig. 7. Actual and forecasted prices with modeling of cross-market economies (U.S. and U.K. stocks) with intra-events "U.S. Elections" and "Scottish independence referendum" and inter-event "Gaza Under Attack" and "Lahore Blast" and their corresponding macroeconomics.

Table 6
Results of the MEIG on superpower Economies with intra-events "U.S. Elections" and "Hong Kong Protests" and inter-event "Scottish independence referendum" and "Brussels Airport Explosion".

Exp#	MAE	MSE	RMSE	Macro	Inter Events	Intra Events	Inter/Intra Events	Forecast Horizon
1	0.0159	0.00044	0.02105	×	√	×	×	1
2	0.01195	0.00027	0.01656	×	×	√	×	1
3	0.01155	0.00026	0.01621	×	×	×	√	1
4	0.01149	0.00026	0.01604	GDP	×	×	√	1
5	0.0143	0.00036	0.01886	GDP	×	×	×	1
6	0.0132	0.00032	0.0118	Inflation	×	×	√	1
7	0.01662	0.00046	0.02138	Inflation	×	×	×	1
8	0.01217	0.00028	0.01681	Interest	×	×	√	1
9	0.01138	0.00025	0.01585	Interest	×	×	×	1
10	0.01361	0.00035	0.01881	UNRATE	×	×	√	1
11	0.01935	0.00058	0.02414	UNRATE	×	×	×	1

intra-inter event sentiments, and macroeconomic indicators. More explicitly, the statistics gathered by federal and state departments, commercial groups, and bureaus are known as macroeconomic indicators. They provide information about the state of economies generally, including GDP, the unemployment rate, interest rates, inflation, and CPI.

3.3.1. Node representation of MEIG-GNN-Macro data

The collected macroeconomic data are listed below, and a summary is provided in Table 2.

3.3.1.1. Gross Domestic Product (GDP). To indicate the macroeconomic performance, GDP is one of the key indicators since it computes the overall market value by involving the goods as well as services built in the country during a specific timeframe for instance, in a year or quarter. The development as well as financial health of the country is strongly indicated by GDP, and it is analyzed by investors to determine the strength of the economy. For instance, when there is an increase in the value of GDP, it shows a rise in the value of corporate profits, the high value of stock prices, and currency. In this research, the GDP of different countries has been collected to model with their particular stocks at intra-level graphs. Mathematically, the multivariate time formulation on each node intra-graph by including GDP is provided in Eq. (8):

$$y_d{}^s = f(X^s, GDP, Intra - InterSentiment) \tag{8}$$

In above Eq. (8),$X^s = (x^s_{d-p}, \cdots.., x^s_{d-1})$ represents past stock values, $GDP = (GDP_{d-p}, \cdots.., GDP_{d-1})$ represent GDP history i.e. time series of GDP values over a specific time frame according to an intra-graph of a particular country, for instance, the GDP of the U.S. is utilized on an intra-graph of the U.S. stock market namely SP500. The $Sentiment = (Sentiment_{d-p}, \cdots.., Sentiment_{d-1})$ represents intra and inter-event sentiment history.

3.3.1.2. Unemployment rate (UNRATE). This indicator measures the proportion of total unemployed individuals as a percentage of the workforce. The unemployment rate has an impact on stock prices e.g. it is observed that when the rate of unemployment increases, it will also cause a decrease in the inflation rate which will ultimately become the reason for high stock prices (Gonzalo & Taamouti, 2017). In this research, unemployment rates of different countries have been collected to model with their particular stocks at intra-level graphs. Mathematically, the multivariate time formulation on each node intra-graph by including UNRATE is provided in Eq. (9):

$$y_d{}^s = f(X^s, UNRATE, Intra - InterSentiment) \tag{9}$$

In the above Eq. (9), $X^s = (x^s_{d-p}, \cdots.., x^s_{d-1})$ represents past stock values, $(UNRATE_{d-p}, \cdots\cdots.UNRATE_{d-1})$ is the time series of UNRATE values over the time period according to the intra-graph of the country, for example, the UNRATE of the U.K. is utilized on an intra-graph of the U.K. stocks market namely the FTSE-100 Index while the $Sentiment = (Sentiment_{d-p}, \cdots.., Sentiment_{d-1})$ represents intra and inter-event sentiment history.

3.3.1.3. Interest rate. This indicator represents the spending that is charged by a lender from a borrower and is generally defined as a proportion of the principal amount. More explicitly, it is one of the effective instruments determined by central banks for regulating the country's economy. Interest rates have a big influence on stock market prices, and asset values, including investment choices in the financial markets. In this research, unemployment rates of different countries have been collected to model with their particular stocks at intra-level graphs. Mathematically, the multivariate time formulation on each node intra-graph by including the interest rate is provided in Eq. (10):

$$y_d{}^s = f(X^s, InterestRate, Intra - InterSentiment) \tag{10}$$

3.3.2. Inter-intra-level events on nodes

To incorporate the sentiments of inter-intra level events, tweets are extracted against different events that occur in each country e.g. sentiments of tweets against the U.S. election which is an intra-event occurring locally in the U.S. and likewise, the inter-events for U.S. can be a Hong Kong protests in China. Hence, on the intra-graph model, both intra-inter level events are included as multi-variate time series in addition to macro data as node features. For instance, U.S. events include "Brexit", "Hong Kong Protest", "US Election", "Mexican Election", and "Obama-Romney".

3.4. Graph convolutions

Graph structured data, based on graph signal theory, should be represented using graph convolution neural networks that are specifically built to learn from this sort of data. To obtain meaningful information from nodes by considering their neighboring nodes at a depth defined as d from the data following the graph structure, then the utilization of the GCN model is justified and consistent in comparison with models that are not able to acquire information from this type of data. In the latest research studies on GNN, different researchers have improved the model to draw higher-level representations from different architectures of graph models. At the initial level, the concept of graph convolution is first introduced in the spectral domain, by following the theory of convolution operation designed to be applied on the images. More precisely, the decomposition of graph Laplacian matrix is carried out and via this, the matrix is translated from $L = I_N - D^{-\frac{1}{2}}AD^{-\frac{1}{2}} \in \mathbb{R}^{N\times N}$ to $L = U\Lambda U^T$ and this process is succeeded by the operation of normalization. During this operation, the details of the graph structure are contained in the graph Fourier basis U in which D indicates the degree matrix of A, wherein Λ and U portray the eigenvalues as well as eigenvalue matrix. Mathematically, $x \in \mathbb{R}^N$ in the initial step indicates that the graph signal is rendered into the spectral domain. This is carried out by employing the technique of graph Fourier U after operating the

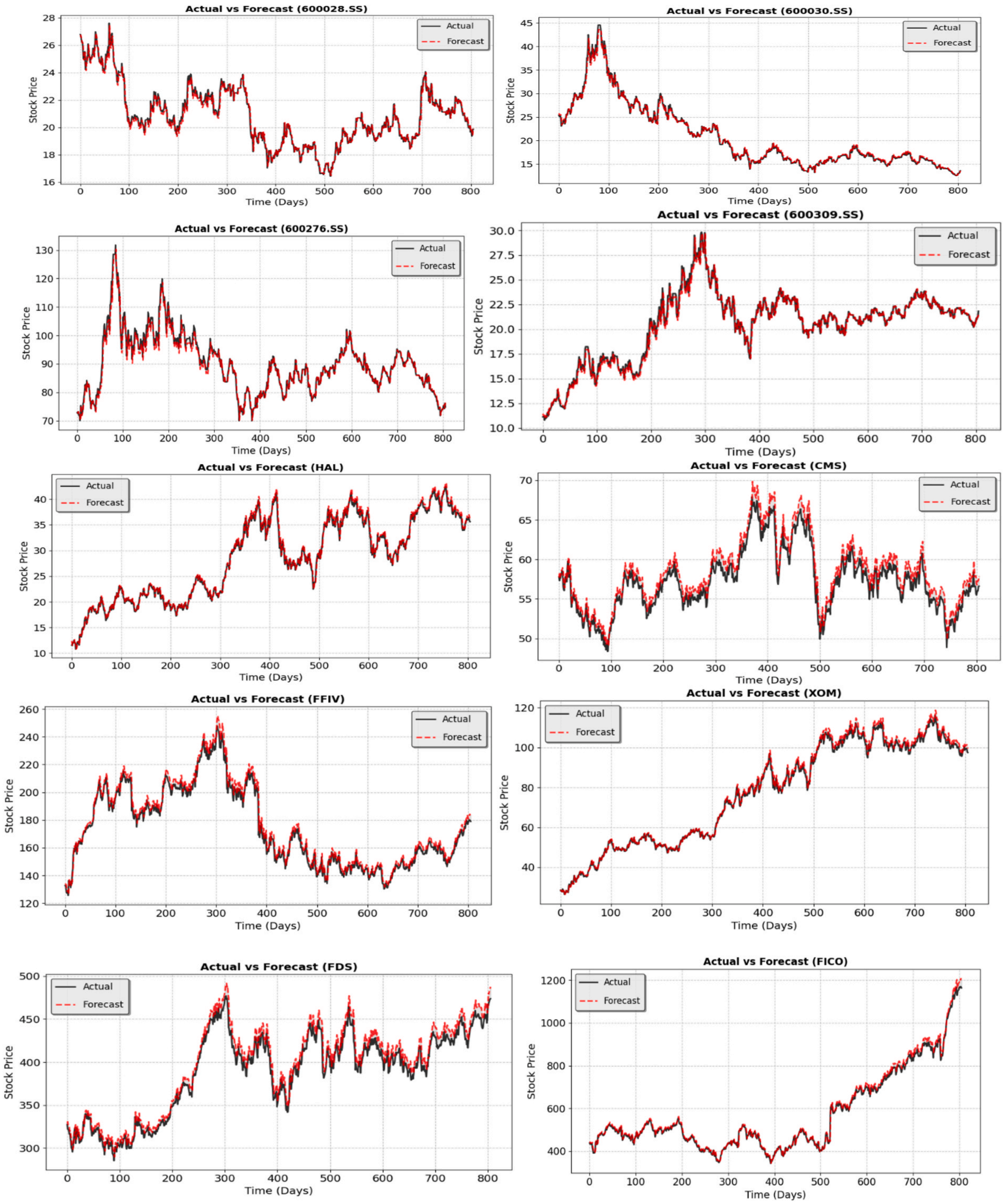

Fig. 8. Actual and forecasted prices with modeling of cross-market economies (U.S. and China stocks) with intra-events "U.S. Elections" and "Hong Kong Protests" and inter-event "Scottish independence referendum" and "Brussels Airport Explosion" and their corresponding macroeconomics.

filtering kernel Θ. After this operation, another transformation is performed in which it is converted back to the inverse graph Fourier basis U^T. Eq. (11) describes the outcome of the convolution process:

$$y = \Theta *_{\mathscr{G}} x = U\Theta U^T x \tag{11}$$

In the above Eq. (11), $*_{\mathscr{G}}$ indicates the operation of graph convolution. The kernel Θ makes sure that nodes of the graph maintain the N weights for carrying out the procedure of convolution. To obtain the k-hop convolution, the value of the kernel Θ is constrained in accordance with the polynomial of eigenvalue.

$$y = \Theta(\Lambda) *_{\mathscr{G}} x = U\left(\sum_{k=0}^{K-1} \theta_k \Lambda^k\right) U^T x = \sum_{k=0}^{K-1} \theta_k \mathrm{L}^k x \tag{12}$$

In the above Eq. (12), $\boldsymbol{\theta}$ is tied with $\mathbb{R}^{\boldsymbol{K}}$ known as vectors of polynomial coefficients. Furthermore, the $\boldsymbol{k}$ indicates the total size of the kernel during the convolution operation. This kind of operation initially introduced spectral convolution which requires a lot of parameters and is hence computationally costly since it necessitates extensive

Table 7
Results of the MEIG Model on cross-market correlations between developed and emerging economies (U.S. and P.K.) with intra events "U.S. Elections" and "Lahore Blast" and inter-evens are "Nepal Earthquake" and "Gaza Under Attack".

Exp#	MAE	MSE	RMSE	Macro	Inter Events	Intra Events	Inter/Intra Events	Forecast Horizon
1	0.01231	0.00029	0.01712	×	√	×	×	1
2	0.01099	0.00024	0.01563	×	×	√	×	1
3	0.01107	0.00025	0.01573	×	×	×	√	1
4	0.01128	0.00025	0.01575	GDP	×	×	√	1
5	0.01098	0.00024	0.01557	GDP	×	×	×	1
6	0.0125	0.00029	0.01713	Inflation	×	×	√	1
7	0.01423	0.00038	0.0195	Inflation	×	×	×	1
8	0.02036	0.0006	0.02459	Interest	×	×	√	1
9	0.01129	0.00025	0.01574	Interest	×	×	×	1
10	0.01173	0.00027	0.01629	UNRATE	×	×	√	1
11	0.01252	0.00029	0.01713	UNRATE	×	×	×	1

calculations for input graphs. The solution to this problem is the incorporation of Chebyshev polynomials into these kernels and additionally, the layer-by-layer convolution technique is limited to $K = 1$. With this adjustment, the issue of overfitting which occurs in graph models containing a large number of nodes and degree ranges is also reduced and hence the resulting models are known as GNNs. The GCN model transforms the Eq. (13) into a layer that is fully connected with inherent convolutional layers.

$$H^{l+1} = Relu\left(\widehat{A}H^lW^l\right) \tag{13}$$

In the above Eq. (13), $\widehat{A} = \widehat{D}^{-\frac{1}{2}}\widehat{A}\widehat{D}^{-\frac{1}{2}}$ and $\widehat{A} = A + I_N$, including, $\widehat{A}$ comprises of the adjacency matrix according to the graph which is provided at the input. The node-to-node connections are also included. Furthermore, I_N reveals the identity matrix and $\widehat{D} = \sum_j \widehat{A}_{i,j}$ possesses weights optimized by an optimizer represented as W^l. Therefore, the previous Eq. (13) is then rewritten as Eq. (14):

$$H^{l+1} = \rho\left(\sum_{k=0}^{K-1}\theta_k \mathrm{L}^k\right)H^lW^l \tag{14}$$

In the above Eq. (14), the input graph is denoted by L comprising nodes and edges between nodes, while $H^l \in \mathbb{R}^{N\times F}$ is the value provided at $l - th$ and ReLu activation is represented by $\rho\,(\cdot)$. The very first phase in GCN is collecting information about nearby stocks via multiplying both Laplacian and the feature matrices. Beyond that, a layer that is fully connected is put together to collect features and build abstract illustrations of every individual stock.

3.5. MEIG—LSTM layers

After acquiring the representation of the node followed by applying the graph convolution which extracts the useful spatial information, the LSTM layers are added to process temporal information on each node. Each node represents particular stock data comprises historical stock prices, macroeconomic indicators, and event sentiment. All these variables are framed in a multivariate time series.

In particular, the LSTM model, also known as Long short-term memory networks, is a type of deep learning algorithm that processes sequencing data and is thought to be a strengthened form of Recurrent Neural Networks (RNNs). The inclusion of memory cells into the original RNNs will turn RNNs into LSTM cells which makes them good in learning long-range dependencies. In comparison with RNN, LSTM oversees the issue of vanishing gradients in an optimized way. Its architecture includes three gates namely input, output, and forgot gate. The objective of these gates is to maintain track of information that streams in and out throughout various time intervals. The primary work of the forgot gate is to remove the information from memory that is no longer required. The outcome is figured out by the output gate, and this is computed as follows:

$$f_t = \sigma\left(W_f.[h_{t-1}, x_t] + b_f\right) \tag{15}$$

In the above Eq. (15), the weights and biases of the forgot gate are represented by W_f and b_f.

Here the input x_t shows the multi-variate time series consisting of historical price data, macroeconomic indicators, and event sentiments. The outputs at previous time steps are denoted by h_{t-1} and the whole output is passed through the sigmoid activation. The final value generated at prior time steps along with the present time step is passed through the input gate, which provides output along with the candidate cell state.

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \tag{16}$$

$$\widehat{C}_t = tanh(W_C.[h_{t-1}, x_t] + b_C) \tag{17}$$

The weighs linked to the input gate is denoted as W_i and the current cell is updated as per the following equation:

$$C_t = (f_t{}^*C_{t-1} + i_t{}^*\widehat{C}_t) \tag{18}$$

Following on, the final two things i.e., input x_t and h_{t-1} are employed to compute the output at the output gate as follows:

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \tag{19}$$

W_o and b_o in the above Eq. (19) represent the bias terms along with weights connected with the output gate, respectively. The ultimate result of the LSTM is estimated by using the final result of the output gate and the present

state of the cell. It is defined in Eq. (20):

$$h_t = o_t{}^*tanh(C_t) \tag{20}$$

In this research, there are two consecutive LSTM layers are added with hidden units 64 and 32 along with "ReLu activation". After an LSTM layer, dense layers are added in MEIG-GNN with linear activation for stock price forecasting.

3.6. MEIG—Cross graph attention layer (CGAT)

Cross-graph attention layer is proposed as shown in Fig. 5 in the MEIG framework to manage the interplay between different market graphs. To dynamically adjust the importance of graphs at intra-levels in comparison with inter-level, this CGAT layer assigns weights to different graphs to make sure that while forecasting stock prices, the most relevant geographical and structural relationships are underlined. This layer highlights the importance of every market's intra (local) graph including global (inter graph). More precisely, three parallel graph convolution layers are designed to operate on intra-graphs and as well as inter-graph. Afterwards, the learnable attention mechanism is designed in which weights are assigned to each graph and these are optimized during the

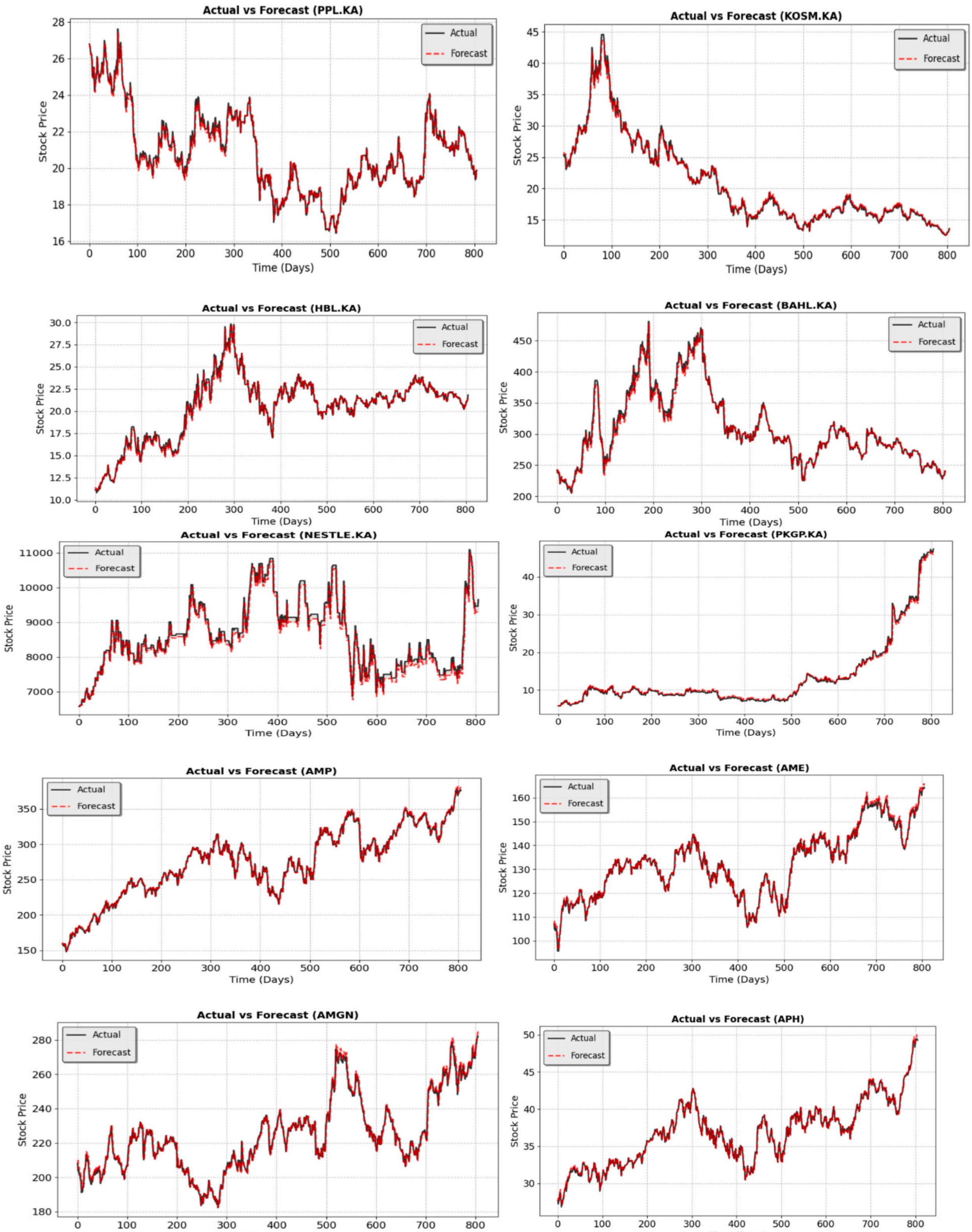

Fig. 9. Actual and forecasted prices with modeling of cross-market economies (U.S. and P.K) with intra-events "US Earthquake" and "Lahore Blast" while the inter-events are "Nepal Earthquake" and "Gaza Under Attack" and their corresponding macroeconomics.

training process. To make these weights meaningful, SoftMax-based normalization is applied to make sure that these weights are sum to one. Mathematically, consider an intra-graph supposed for the U.S. and U.K. and an inter-graph passes through the graph convolution layers as $GraphConv_{intragraph,U.S.}$, and $GraphConv_{Intra-graph,U.k.}$, and global graph as $GraphConv_{inter-graph.}$. The output of these graph convolution layers on an input matrix X can be denoted as Z as shown below:

Table 8
Results of the MEIG Model on cross-market correlations between developed and emerging economies (**U.K. and Turkey)** with intra-events "Cyprus Hijacked Plane 2016" and "Scottish independence referendum", and inter-events "Hurricane Sandy 2012" and "Irish General Elections 2016".

Exp#	MAE	MSE	RMSE	Data	Inter Events	Intra Events	Inter/Intra Events	Forecast Horizon
1	0.00968	0.00022	0.01495	Inter event	√	×	×	1
2	0.0098	0.00023	0.01519	Intra event	×	√	×	1
3	0.01161	0.0003	0.01736	Inter/intra both	×	×	√	1
4	0.0133	0.00037	0.01927	GDP	×	×	√	1
5	0.0106	0.00026	0.016	GDP	×	×	×	1
6	0.01297	0.00036	0.01908	Inflation	×	×	√	1
7	0.0143	0.00041	0.02019	Inflation	×	×	×	1
8	0.01338	0.00033	0.01827	Interest	×	×	√	1
9	0.01197	0.0004	0.02009	Interest	×	×	×	1
10	0.01164	0.00036	0.01887	UNRATE	×	×	√	1
11	0.01171	0.00036	0.01909	UNRATE	×	×	×	1

$$Z_{U.S} = GraphConv_{ntragraph,U.S.}(X), Z_{U.K} = GraphConv_{Intragraph,U.S.}(X), Z_{Inter-Graph} = GraphConv_{Intergraph,U.S.}(X) \tag{21}$$

In the next step, for each graph attention scores are calculated for the graph denoted as α as shown below:

$$\alpha = Softmax(w) \tag{22}$$

In the above equation, w denotes the set of learnable weights connected with each level graph. Next, a weighted aggregate is calculated from the entire result Z from each one of the distinct graph convolutions:

$$Z = \alpha_{US.}Z_{U.S} + \alpha_{UK.}Z_{U.S} + \alpha_{inter.}Z_{inter} \tag{23}$$

As a result, at various time stages, the MEIG model can continually highlight the most important market interactions.

4. Experiments and Discussions

This section demonstrates the proposed MEIG-GNN model's findings, the details of the dataset utilized, evaluation metrics, and an explanation of the results that were obtained.

4.1. Dataset and statistics

In this study, stock indexes belonging to five different stock markets are taken into consideration for experimentation. More precisely, the stock market of Pakistan includes KSE-100 stocks, the stock market of U.K includes 100 stocks from FTSE-100, the stock market of China includes 50 stocks from SSE-50, the stock market of Turkey includes 100 stocks from Borsa Istanbul Index (BISET-100). While from the U.S. stock market, 500 stocks from the SP500 Index are included.

Moreover, investor sentiments are computed by utilizing an extensive dataset of tweets related to different intra-inter events from 2012 to 2016. The details of the markets with their associated intra-events considered are provided in Table 3. The total number of tweets against each intra-inter event is provided in Table 4. In addition, the period for historical closing prices includes the data of 12 years from 2008 to 2020. In addition, the Jerque-Bera test for normality has been applied to the some 15 volatile and least 15 volatile stocks of U.S., China, Pakistan, Turkey, and U.K. stock markets as shown in Fig. 6. The Jarque-Bera test is a good-fit metric that determines if the collection of data's kurtosis, as well as skewness, corresponds to a normal distribution or not. The orange circles in Fig. 6 show the test-statistic value of Jerque-Bera for each stock while the blue is a constant line on value 0 as reference. The stocks having a p-value less than 1 % significance level are denoted by "*" in Fig. 6. Furthermore, the computational complexity in terms of space and time complexity of the proposed MEIG model allows for efficient execution. The simulations were carried out on Kaggle, and every simulation took approximately 13.36 s (0.22 min) on a GPU P100. The model makes good use of resources, using 15.4 GiB of GPU RAM (out of 16 GiB) and limiting CPU usage to a minimum. Furthermore, it has an acceptable memory usage, employing 2.1 GiB RAM and 2.3 GiB disk space, validating its scalability and usefulness for real-time stock price forecasting.

4.2. Evaluation metrics

The evaluation metrics used to evaluate the results of the proposed MEIG model are described below:

4.2.1. Mean absolute error (MAE)

The MAE absolute error is one of the famous metrics used to assess the accuracy of forecasting models. This has been computed as a difference between actual stock prices and stock prices predicted by the MEIG model. MAE error provides the same importance to all errors. The mathematical formula utilized to compute the error of MEIG is given below:

$$MAE = \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{n} \tag{24}$$

In the above Eq. (24), n shows the total example of the testing set while y_i is the original stock price and $\hat{y}_i$ is stock price predicted by the MEIG model.

4.2.2. Mean squared error (MSE)

The MSE, like the MAE, is a widely used statistic for evaluating the errors of forecasting models. The error of the MEIG model is calculated as a squared error between the actual and predicted stock prices. It is often referred to as mean squared deviation (MSD). The mathematical formula used to compute the error of the MEIG model is as follows:

$$MSE = \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n} \tag{25}$$

In the above Eq. (25), n shows the total example of the testing set while y_i is the original stock price and $\hat{y}_i$ is stock price predicted by the MEIG model.

4.2.3. Root mean squared error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}} \tag{26}$$

The RMSE is also one of the important and most employed metrics for computing the errors of forecasting models by applying the square root to the MSE value. The mathematical formula for RMSE is given below:

In the above Eq. (26), n shows the total example of the testing set while y_i is the original stock price and $\hat{y}_i$ is stock price predicted by the MEIG model.

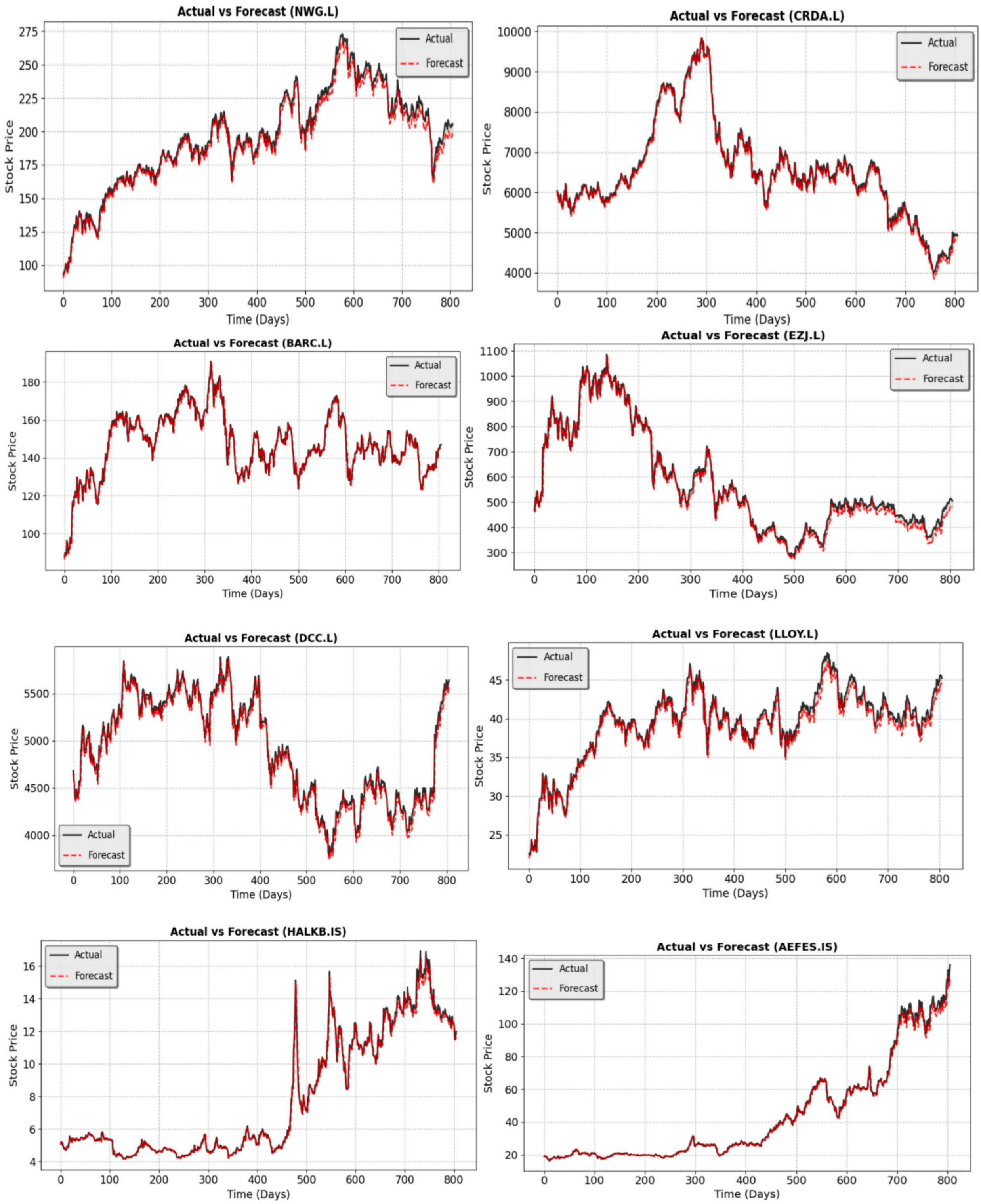

Fig. 10. Actual and forecasted prices of modeling cross-market economies (U.K and Turkey) “Scottish independence referendum“, and “Cyprus Hijacked Plane 2016” while inter-events are “Hurricane Sandy 2012” and “Irish General Elections 2016” along with their corresponding macroeconomics.

4.3. Impact of Cross-Border market correlations in developed economies (U.S and UK)

Initially, the results of the proposed MEIG model are investigated to study the cross-border market correlation among the top developed economies (i.e. U.S.) having the highest GDP value with the U.K. having good GDP (comparatively less than China). The results of the proposed MEIG model by considering the U.S. and U.K. with their separate intra-graph branches as well as their global inter-graph model are provided in Table 5. More precisely, in this setup, the inter-events include “Gaza Under Attack“ which is the terrorist attack event in Gaza located in the southwest corner of Israel, and “Lahore Blast” which is also a terrorist

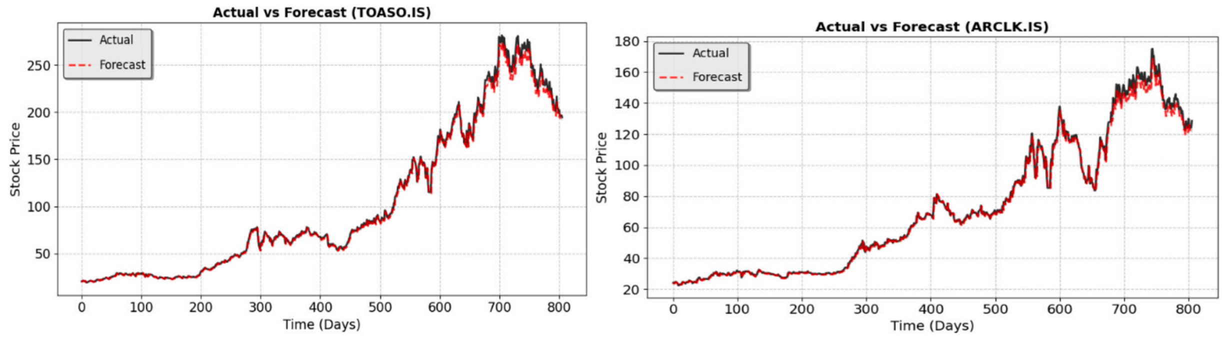

Fig. 10. (*continued*).

Table 9
Results of the MEIG Model on cross-market correlations between emerging economies (**Turkey and Pakistan)** with intra-events "Cyprus Hijacked Plane 2016" and "Lahore Blast" and inter-events "Hurricane Sandy 2012" and "Irish General Elections 2016".

Exp#	MAE	MSE	RMSE	Data	Inter Events	Intra Events	Inter/Intra Events	Forecast Horizon
1	0.00947	0.00024	0.01533	×	√	×	×	1
2	0.01037	0.00026	0.01611	×	×	√	×	1
3	0.01163	0.00035	0.01877	×	×	×	√	1
4	0.01613	0.00052	0.02291	GDP	×	×	√	1
5	0.01238	0.0005	0.0224	GDP	×	×	×	1
6	0.02058	0.0008	0.02827	Inflation	×	×	√	1
7	0.01383	0.00059	0.02428	Inflation	×	×	×	1
8	0.00939	0.00023	0.01509	Interest	×	×	√	1
9	0.00991	0.00025	0.01571	Interest	×	×	×	1
10	0.01135	0.00038	0.01937	UNRATE	×	×	√	1
11	0.00967	0.00025	0.01568	UNRATE	×	×	×	1

event in Pakistan. Likewise, the intra-events occurring locally in the U.S. and U.K. are the "U.S. Elections" and "Scottish independence referendum" in the U.K. The experimentation was carried out in a range of settings, including modeling only intra-events, only inter-events, or both, as well as macroeconomic factors specific to that country into the nodes of the stock markets. It is observed from results that when intra-market events (for example, U.S. elections and Scottish independence referendum") and inter-market events ("Gaza Under Attack" and "Lahore Blast") are incorporated in the MEIG model, the error values are the lowest such as experiment 08 in Table 5. This suggests that including both inter and intra-events modeling improves the ability of the MEIG to capture the entire range of factors influencing stock prices in cross-market economies such as the U.S. and the U.K. However, it is observed that by including the macroeconomic variable "inflation", the error values are a little bit higher i.e. 0.01619 MAE error, in comparison with other macroeconomic variables. Because inflation is naturally more volatile and can fluctuate owing to various unpredictable variables, such as abrupt fluctuations in commodity prices (e.g., oil). This inflation rate varies according to U.S. and U.K. economies' trade as well as import–export dynamics. Overall, the results of the proposed MEIG model in learning cross-border interactions among the developed economies i.e. U.S. and U.K. show the significant level of financial interdependence that exists between the U.S. and U.K. markets. In addition, both markets are comparatively less volatile than developing markets, which contributed to understanding why the model performs better at predicting stock prices. Moreover, the actual and predicted prices of the MEIG model are also plotted in this case as shown in Fig. 7. It is observed from Fig. 7 that forecasted prices are closely aligned with the actual prices of stocks for both the U.S. and U.K.

4.4. Impact of Cross-Border market correlations between superpower economies (U.S and China)

In this second experiment, the outcomes of the proposed MEIG model were examined through an analysis of the cross-market dynamics among the strongest economies possessing the highest GDP values. The U.S. has the largest economy, and China has the second-largest world economy. This pair shows the most important part of the study for global financial markets since the two countries are acknowledged as superpowers with substantial impacts on world economic businesses. The results of the proposed MEIG model on this pair of U.S. and China are provided in Table 6. The intra-events, in this case, i.e. U.S. and China are "U.S Elections ", and from China, the intra-event is "Hong Kong" protests while the inter-events are "Scottish independence referendum" and "Brussels Airport Explosion". The results with this experimental setup are also good like the previous U.S. and U.K. pair. The findings indicate that when intra-inter events are involved in the experiments, the error values are more minimal in comparison with experiments in which only macroeconomic variables are involved, e.g. the MAE error is 0.0132 when intra-inter events are included with inflation while with only inflation the error is a little bit high i.e. 0.01662. This suggests that the occurrence of noteworthy market events enhances comprehension of market sentiment and volatility, enabling more precise forecasting in conditions of economic ambiguity. Moreover, among the all-macroeconomic conditions, again the inflation induces some uncertainty and will lead to some high errors. On the other hand, the interest rate exhibits strong performance when compared to all other macroeconomic variables, suggesting that interest rates have a greater impact on stock prices in cross-market interactions, particularly between major economies like the U.S. and U.K., or the U.S. and China. If a comparison has been done between the U.S. and U.K. or the U.S. and China, then the results of the proposed MEIG model show good results on the U.S. and U. K. pair in comparison with the U.S. and China. This is due to the reason that China maintains a more rigid economic structure than the U.S., which has a market-driven economy with little government interference, hence both the U.S. and China have diverging economic models. Even though both China and the United States are global superpowers, the financial systems of both countries are less interconnected than the U.S. and U.K. Likewise, when unemployment (UNRATE) is modeled the error in comparison with other all experiments is a little bit high i.e.

Fig. 11. Actual and forecasted prices with modeling of cross-market economies (Turkey and Pakistan) "Cyprus Hijacked Plane 2016" and "Lahore Blast 2016", while inter-events are "Hurricane Sandy 2012" and "Irish General Elections 2016" along with their corresponding macroeconomics.

0.0193. This shows that both U.S. and China labor markets are operated in different economic settings hence showing less cross-market correlations. Moreover, the actual and predicted prices of the MEIG model are also plotted in this case as shown in Fig. 8. It is observed from Fig. 8 that forecasted prices are closely aligned with the actual prices of stocks for both the U.S. and China.

4.5. Results with Cross-Market correlations between developed and emerging economies (U.S. And P.K)

In this third experimental setup, the cross-market correlations of developed and emerging economies are studied i.e. U.S. and Pakistan. More precisely, Pakistan is an emerging market and in comparison, to the U.S. it has less GDP value and its financial market is less mature, showing volatility, and is more responsive to economic fluctuations happening in the world. This experiment shows how stock price forecasting has been influenced if the cross-market interactions among developed and emerging markets have been modeled. The results of this setup are provided in Table 7 and in this setup, the intra-events are "U.S. Elections" and "Lahore Blast", while the inter-events are "Nepal Earthquake" and "Gaza Under Attack". Overall, the results show minimal error values when these intra-inter events are modeled including macroeconomic data.

The minimal error values are observed when intra-events are

Table 10
Results of the MEIG Model on selected graph nodes representing FTSE stocks.

Stock	MAE	MSE	RMSE	Stock	MAE	MSE	RMSE
NWG.L	0.00179	0.0001	0.00217	**BME.L**	0.0149	0.00038	0.01961
SDR.L	0.01244	0.00026	0.01608	**HSBA.L**	0.01251	0.00028	0.01661
STAN.L	0.01065	0.0002	0.01417	**LGEN.L**	0.01296	0.00029	0.01698
CRDA.L	0.01123	0.0002	0.01417	**CCH.L**	0.01452	0.00039	0.01975
BARC.L	0.00823	0.00013	0.01124	**HWDN.L**	0.01243	0.00024	0.01563
EZJ.L	0.01328	0.00028	0.0166	**GLEN.L**	0.01441	0.00035	0.01883
DCC.L	0.0115	0.00022	0.01489	**VTY.L**	0.0147	0.00036	0.01897
LLOY.L	0.00403	0.00002	0.00498	**PRU.L**	0.01458	0.00038	0.01951
CNA.L	0.0077	0.0001	0.00996	**FRAS.L**	0.0122	0.00031	0.0176
MNG.L	0.01707	0.0005	0.02231	**FCIT.L**	0.01026	0.00017	0.01315
IAG.L	0.01097	0.00017	0.01287	**PSN.L**	0.01298	0.00028	0.01672
MNDI.L	0.01269	0.00028	0.01669	**NXT.L**	0.01288	0.00028	0.01666
ANTO.L	0.01642	0.00046	0.02138	**III.L**	0.01009	0.00016	0.01262
BEZ.L	0.01199	0.00026	0.01605	**HSX.L**	0.0103	0.00017	0.01299
IHG.L	0.01139	0.00021	0.01445	**IMI.L**	0.01253	0.00028	0.01668
WPP.L	0.01146	0.00021	0.01455	**RTO.L**	0.01157	0.00027	0.0164
WEIR.L	0.01401	0.00032	0.01777	**ENT.L**	0.0127	0.00029	0.01715
FRES.L	0.01126	0.00022	0.01475	**PSH.L**	0.01303	0.00027	0.01648
MRO.L	0.01228	0.00027	0.01646	**SHEL.L**	0.01312	0.00029	0.0171

Table 11
Results of the MEIG Model on selected graph nodes representing SP500 stocks.

Stock	MAE	MSE	RMSE	Stock	MAE	MSE	RMSE
MMM	0.00854	0.00014	0.01162	**GOOGL**	0.01288	0.0003	0.01736
AOS	0.01162	0.00024	0.01535	**GOOG**	0.01284	0.0003	0.01733
ABT	0.01044	0.0002	0.01405	**MO**	0.00967	0.0002	0.01401
ABBV	0.00959	0.00018	0.01337	**AMZN**	0.0133	0.00032	0.01797
ACN	0.00961	0.00017	0.01309	**AMCR**	0.01531	0.00044	0.0209
ADBE	0.01183	0.00027	0.01644	**AEE**	0.01107	0.00021	0.01454
AMD	0.01485	0.00041	0.02024	**AEP**	0.01021	0.00019	0.01365
AES	0.0144	0.00036	0.01895	**AXP**	0.01286	0.00031	0.01751
AFL	0.00827	0.00012	0.01118	**AIG**	0.00096	0.00001	0.00127
A	0.011	0.00021	0.01463	**AMT**	0.01128	0.00022	0.01471
APD	0.01162	0.00027	0.01632	**AWK**	0.01078	0.0002	0.01407
ABNB	0.02497	0.00122	0.03499	**AMP**	0.01084	0.00021	0.01437
AKAM	0.01186	0.00028	0.01687	**AME**	0.00982	0.00016	0.01266
ALB	0.0156	0.00045	0.02123	**AMGN**	0.00949	0.00016	0.01278
ARE	0.01069	0.00021	0.01459	**APH**	0.00931	0.00015	0.01206
ALGN	0.01308	0.00036	0.0189	**ADI**	0.01321	0.00029	0.01708
ALLE	0.0142	0.00036	0.01895	**ANSS**	0.01351	0.00034	0.01835
LNT	0.01139	0.00021	0.01459	**AON**	0.01112	0.00023	0.01516
ALL	0.01141	0.00024	0.01543	**APA**	0.00746	0.0001	0.00984

Table 12
Results of the MEIG Model on selected graph nodes representing KSE-50 stocks.

Stock	MAE	MSE	RMSE	Stock	MAE	MSE	RMSE
PPL.KA	0.00425	5.00E-05	0.00694	**YOUW.KA**	0.00775	0.00017	0.01288
KOSM.KA	0.00893	0.00017	0.01317	**NCPL.KA**	0.01093	0.00024	0.01544
OGDC.KA	0.0061	7.00E-05	0.00834	**UNITY.KA**	0.00592	8.00E-05	0.00919
MLCF.KA	0.00511	7.00E-05	0.0082	**MARI.KA**	0.00645	9.00E-05	0.00968
CNERGY.KA	0.00654	9.00E-05	0.00923	**MEBL.KA**	0.01117	0.0003	0.01731
DGKC.KA	0.01092	0.00026	0.01628	**PSX.KA**	0.00388	3.00E-05	0.00573
PSO.KA	0.00741	0.00011	0.01071	**PIBTL.KA**	0.00537	6.00E-05	0.00803
FFBL.KA	0.00384	3.00E-05	0.00559	**SEARL.KA**	0.01525	0.00047	0.02169
PAEL.KA	0.0052	6.00E-05	0.00766	**TRG.KA**	0.00668	0.00013	0.01118
FFC.KA	0.00832	0.00014	0.01184	**NPL.KA**	0.00915	0.00019	0.01367
NML.KA	0.00539	6.00E-05	0.00795	**FATIMA.KA**	0.0078	0.00017	0.01301
HBL.KA	0.0068	0.0001	0.0101	**FABL.KA**	0.00781	0.00014	0.01182
BAHL.KA	0.00123	0.0001	0.00199	**KAPCO.KA**	0.01107	0.00026	0.0162
BOP.KA	0.00946	0.00023	0.01529	**ATRL.KA**	0.00576	7.00E-05	0.00857
PTC.KA	0.0136	0.00036	0.01905	**UBL.KA**	0.0065	0.0001	0.01003
AVN.KA	0.00668	0.00012	0.01116	**ENGRO.KA**	0.00861	0.00018	0.01333
KEL.KA	0.00515	7.00E-05	0.00852	**EPCL.KA**	0.00642	8.00E-05	0.00921
EFERT.KA	0.00795	0.00014	0.01191	**POL.KA**	0.01276	0.00031	0.01761
SNGP.KA	0.01196	0.00038	0.0195	**PIOC.KA**	0.00637	0.0001	0.00989

Table 13
Results of the MEIG Model on selected graph nodes representing SSE50 stocks.

Stock	MAE	MSE	RMSE	Stock	MAE	MSE	RMSE
600028.SS	0.00962	0.00023	0.01527	**600893.SS**	0.00909	0.00016	0.01276
600030.SS	0.0116	0.00027	0.01631	**600900.SS**	0.01401	0.0004	0.02011
600031.SS	0.01393	0.00041	0.02017	**601012.SS**	0.0151	0.00043	0.02079
600036.SS	0.0075	0.00012	0.01114	**601088.SS**	0.00998	0.00021	0.01462
600048.SS	0.01644	0.00051	0.02256	**601166.SS**	0.01237	0.00031	0.01771
600050.SS	0.00767	0.00015	0.01235	**601225.SS**	0.00707	0.00012	0.01111
600089.SS	0.01154	0.00034	0.01847	**601288.SS**	0.00821	0.00014	0.01165
600104.SS	0.00428	3.00E-05	0.00569	**601318.SS**	0.00487	6.00E-05	0.00746
600111.SS	0.00835	0.00015	0.01239	**601390.SS**	0.00682	0.0001	0.00994
600150.SS	0.01066	0.00025	0.01575	**601398.SS**	0.01214	0.00031	0.01769
600276.SS	0.01243	0.00033	0.0181	**601601.SS**	0.01341	0.00035	0.01868
600309.SS	0.0104	0.00026	0.01626	**601628.SS**	0.01307	0.00037	0.01918
600406.SS	0.0128	0.00035	0.0188	**601633.SS**	0.01093	0.00025	0.01566
600436.SS	0.00973	0.00019	0.01386	**601668.SS**	0.0075	0.00016	0.0125
600438.SS	0.01193	0.00027	0.01656	**601669.SS**	0.00464	4.00E-05	0.00652
600519.SS	0.01417	0.00042	0.02057	**601857.SS**	0.0115	0.00029	0.01694
600690.SS	0.00901	0.00018	0.01351	**601888.SS**	0.0195	0.00065	0.02543
600809.SS	0.01331	0.00041	0.02028	**601899.SS**	0.00865	0.00018	0.01339
600887.SS	0.00909	0.00016	0.01276	**601919.SS**	0.00605	0.00012	0.01084

Table 14
Results of the MEIG Model on selected graph nodes representing BIST stocks.

Stock	MAE	MSE	RMSE	Stock	MAE	MSE	RMSE
GARAN.IS	0.01191	0.00037	0.01926	**PGSUS.IS**	0.01413	0.00055	0.02336
KCHOL.IS	0.01154	0.00041	0.02017	**HALKB.IS**	0.01142	0.00036	0.01888
THYAO.IS	0.01153	0.00041	0.02014	**AEFES.IS**	0.01248	0.00042	0.02056
ISCTR.IS	0.01276	0.00041	0.02014	**TOASO.IS**	0.01281	0.00044	0.02098
FROTO.IS	0.01098	0.00036	0.01894	**ARCLK.IS**	0.01341	0.00045	0.02115
TUPRS.IS	0.01137	0.00035	0.01873	**TAVHL.IS**	0.01029	0.00036	0.01906
BIMAS.IS	0.0112	0.00035	0.01881	**OYAKC.IS**	0.0102	0.00037	0.0192
AKBNK.IS	0.01221	0.00042	0.02059	**MGROS.IS**	0.01099	0.00037	0.01935
ASELS.IS	0.01504	0.00056	0.0236	**AGHOL.IS**	0.00912	0.00029	0.01706
ENKAI.IS	0.01142	0.00035	0.01871	**TTRAK.IS**	0.01127	0.00035	0.01863
YKBNK.IS	0.01323	0.0005	0.02235	**MPARK.IS**	0.01223	0.00044	0.02088
VAKBN.IS	0.01235	0.00039	0.01982	**ENJSA.IS**	0.01386	0.00053	0.02311
SAHOL.IS	0.0136	0.00049	0.02204	**GUBRF.IS**	0.01343	0.00054	0.02314
TCELL.IS	0.01246	0.00044	0.02097	**KOZAL.IS**	0.00825	0.00034	0.0184
SASA.IS	0.01549	0.00054	0.02329	**TURSG.IS**	0.00721	0.00033	0.01821
EREGL.IS	0.0148	0.00057	0.02391	**BRSAN.IS**	0.0094	0.00034	0.01849
TTKOM.IS	0.01026	0.00028	0.01663	**ISMEN.IS**	0.01379	0.00047	0.0216
CCOLA.IS	0.01369	0.00049	0.02202	**PETKM.IS**	0.01112	0.00035	0.0186
SISE.IS	0.01107	0.00034	0.01851	**OTKAR.IS**	0.01104	0.00043	0.02071

Table 15
Results of the Proposed MEIG Model on Large Future Horizon of Forecasting with Cross-market Correlation Learning between U.S. and U.K.

Exp#	MAE	MSE	RMSE	Market Pair	Node Inputs	Forecast Horizon	Input sequence
1	0.0117	0.00024	0.01561	US and UK	Intra/IntraEvents + Daily Price	2	1
2	0.01476	0.00036	0.01907	US and UK	Intra/IntraEvents + Daily Price	2	3
3	0.01292	0.0003	0.0174	US and UK	Intra/IntraEvents + Daily Price	2	5
5	0.01123	0.00025	0.01577	US and UK	Intra/IntraEvents + Daily Price	3	1
6	0.01587	0.00045	0.02129	US and UK	Intra/IntraEvents + Daily Price	3	3
7	0.01391	0.00037	0.01933	US and UK	Intra/IntraEvents + Daily Price	3	5

Table 16
Results of the proposed MEIG model on large future horizon of forecasting with cross-market correlation learning between P.K. and Turkey.

Exp#	MAE	MSE	RMSE	Market Pair	Node Inputs	Forecast Horizon	Input sequence
1	0.01818	0.00124	0.03518	PK and Turkey	Intra/IntraEvents + Daily Price	2	1
2	0.01061	0.0003	0.01719	PK and Turkey	Intra/IntraEvents + Daily Price	2	3
3	0.0093	0.00025	0.01576	PK and Turkey	Intra/IntraEvents + Daily Price	2	5
5	0.01236	0.00039	0.0198	PK and Turkey	Intra/IntraEvents + Daily Price	3	1
6	0.01244	0.00035	0.01865	PK and Turkey	Intra/IntraEvents + Daily Price	3	3
7	0.01366	0.0004	0.02004	PK and Turkey	Intra/IntraEvents + Daily Price	3	5

Table 17
Results of the proposed MEIG model on large future horizon of forecasting with cross-market correlation learning between U.S. and China.

Exp#	MAE	MSE	RMSE	Market Pair	Node Inputs	Forecast Horizon	Input sequence
1	0.01172	0.00026	0.01622	US and China	Intra/IntraEvents + Daily Price	2	1
2	0.01441	0.00036	0.01903	US and China	Intra/IntraEvents + Daily Price	2	3
3	0.01291	0.00032	0.01787	US and China	Intra/IntraEvents + Daily Price	2	5
5	0.01248	0.0003	0.01718	US and China	Intra/IntraEvents + Daily Price	3	1
6	0.02848	0.0017	0.03425	US and China	Intra/IntraEvents + Daily Price	3	3
7	0.01642	0.0045	0.02123	US and China	Intra/IntraEvents + Daily Price	3	5

Table 18
Results of the proposed MEIG Model on large future horizon of forecasting with cross-market correlation learning between U.K. and Turkey.

Exp#	MAE	MSE	RMSE	Market Pair	Node Inputs	Forecast Horizon	Input sequence
1	0.01388	0.00062	0.02481	Turkey and UK	Intra/IntraEvents + Daily Price	2	1
2	0.01157	0.00032	0.01794	Turkey and UK	Intra/IntraEvents + Daily Price	2	3
3	0.01119	0.00031	0.01749	Turkey and UK	Intra/IntraEvents + Daily Price	2	5
5	0.01127	0.00029	0.01704	Turkey and UK	Intra/IntraEvents + Daily Price	3	1
6	0.01213	0.00035	0.01863	Turkey and UK	Intra/IntraEvents + Daily Price	3	3
7	0.01228	0.00033	0.01804	Turkey and UK	Intra/IntraEvents + Daily Price	3	5

Table 19
Results of the proposed MEIG model on large future horizon of forecasting with cross-market correlation learning between U.S and PK.

Exp#	MAE	MSE	RMSE	Market Pair	Node Inputs	Forecast Horizon	Input sequence
1	0.01088	0.00024	0.0154	U.S. and PK	Intra/IntraEvents + Daily Price	2	1
2	0.01237	0.00031	0.01749	U.S. and PK	Intra/IntraEvents + Daily Price	2	3
3	0.01193	0.00029	0.01699	U.S. and PK	Intra/IntraEvents + Daily Price	2	5
5	0.01116	0.00025	0.01566	U.S. and PK	Intra/IntraEvents + Daily Price	3	1
6	0.01199	0.00028	0.01668	U.S. and PK	Intra/IntraEvents + Daily Price	3	3
7	0.01268	0.00031	0.01767	U.S. and PK	Intra/IntraEvents + Daily Price	3	5

modeled and this indicates stock prices of Pakistan are more influenced by their homeland local events, which is about 0.01099 MAE error. Hence, these intra-market events of Pakistan are more significant in analyzing U.S. and Pakistan cross-market interactions. Similarly, when these intra-events are combined with inter-events then the results are also good with an MAE of 0.01107, however, when inter-events are included solely, the performance declines due to the exclusion of intra-events which are more critical in this case. Likewise, the results of U.S. and P.K. pair with their corresponding macroeconomic variables also exhibit fewer error values, but with inflation and interest rate, the error values are a little bit higher since both inflation and interest are volatile in nature in the case of Pakistan in comparison with the U.S. having stable interest and inflation rate. Hence, higher error values are a consequence of the GNN's inability to adequately reflect these divergent inflation patterns between the United States and Pakistan. On the other hand, the cross-market correlations between the U.S. and P.K. with GDP show best results indicating that a key measure of both countries' economic performance is their GDP. The MAE error value with GDP is about 0.01098, which is extremely good and shows the worth of the proposed MEIG model. Moreover, the actual and predicted prices of the MEIG model are also plotted in this case as shown in Fig. 9. It is observed from Fig. 9 that forecasted prices are closely aligned with the actual prices of stocks of both U.S. and P.K.

4.6. Results with cross-market correlations between developed and emerging economies (U.K. and Turkey)

In this experimental setup, the stock price forecasting has been tested by involving the cross-market correlations between Turkey and the U.K. As discussed in the previous experiment, i.e. U.S. and Pakistan, this setup is also a special case of analyzing results between emerging and developed markets. The results of this setup are provided in Table 8. The intra-events, in this case, are "Cyprus Hijacked Plane 2016" and "Scottish independence referendum", while inter-events are "Hurricane Sandy 2012" and "Irish General Elections 2016". The results in Table 8 demonstrate that with intra-inter events as well as with GDP the model shows good results and minimal error values. The same behaviors are observed in previous experiments when U.S. and P.K. stock markets are employed (i.e. emerging and developed). So, this can be deduced that in cross-correlation networks of developing and emerging markets, these inter-intra event factors and GDP are quite important for stock price forecasting. Likewise, the error values with inflation rate are higher in comparison with other variables such as MAE error with inflation and without intra-inter events is 0.0143 while with inflation along with intra-inter events, the MAE error is about 0.01297 respectively. This indicates that with only inflation, the error is somewhat high but when intra-inter events are modeled, then the error subsequently goes down 2 points hence showing the importance of inter-intra events in comparison with macroeconomic data.

More explicitly, the pair between the UK and Turkey demonstrates the challenges in modeling cross-market interactions between emerging and established economies i.e., macroeconomic factors related to inflation bring complexity that raises forecasting errors. Moreover, the actual and predicted prices of the MEIG model are also plotted in this case as shown in Fig. 10. It is observed from Fig. 10 that forecasted prices are closely aligned with the actual prices of stocks in both the U.K. and Turkey.

4.7. Results with cross-market correlations in emerging economies (Turkey and Pakistan)

In this last experimental setup, the results of the proposed MEIG model have been validated against the emerging economies namely Turkey and Pakistan. This analysis demonstrates the connections between two developing economies that are sensitive to economic developments worldwide and have significant levels of volatility along with instability in common. These two countries have significant differences in terms of geographic, political, and economic contexts since

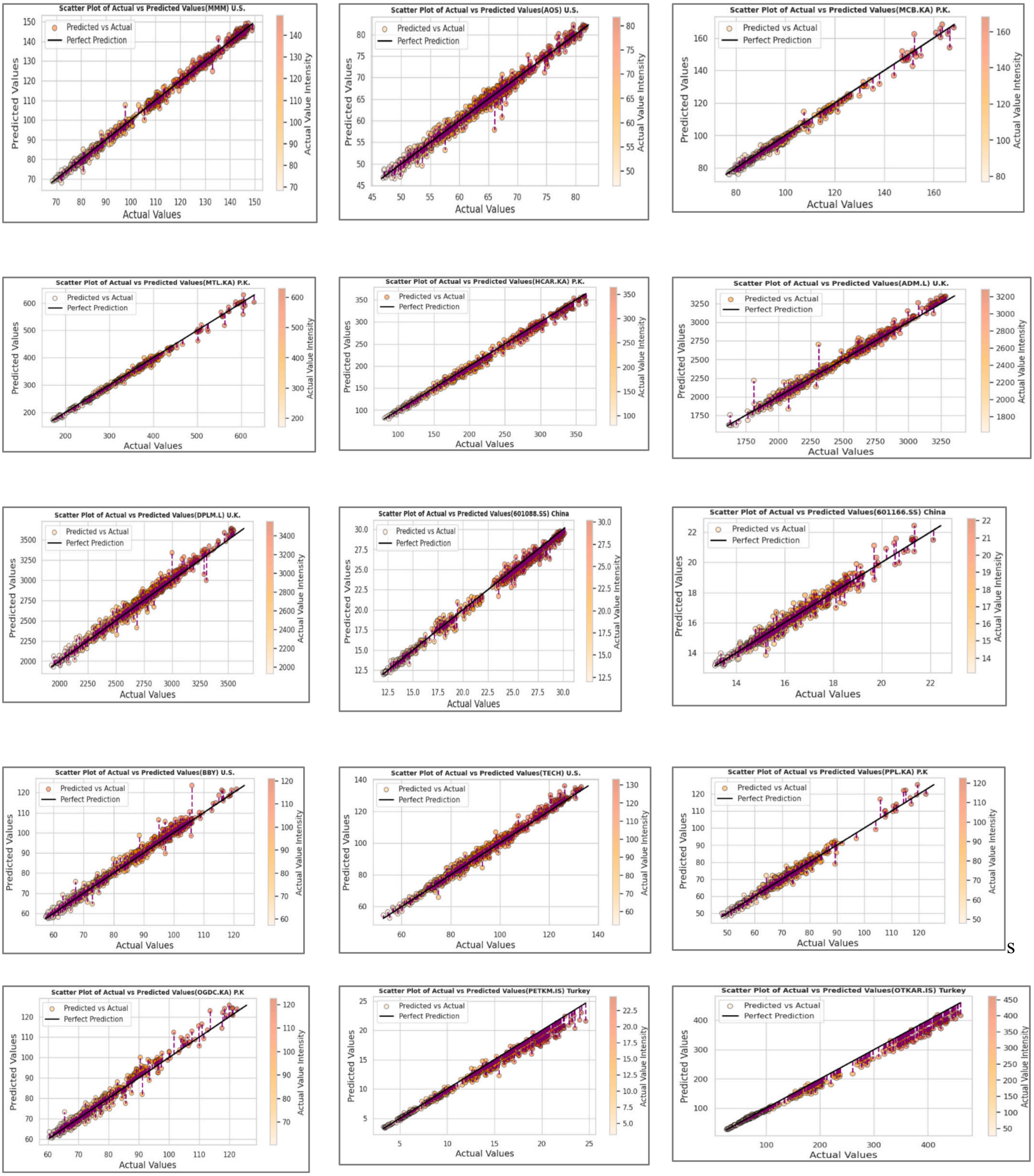

Fig. 12. Scatter plots of predicted stock prices for various stock symbols across different markets.

Turkey is more involved in European and Middle Eastern markets while Pakistan is impacted by South Asian markets. The results of this setup are provided in Table 9. In this setup, the inter-events are “Hurricane Sandy 2012” and “Irish General Elections 2016” while the intra-events are “Cyprus Hijacked Plane 2016” and “Lahore Blast”. The results in Table 9 demonstrate that while learning the cross-country correlation between Pakistan and Turkey, the interest rate with inter-intra events is more important for precise stock price forecasting. For instance, the MAE errors are about 0.00939 and 0.00991. This is because emerging markets are particularly dependent on fluctuations in interest rates in terms of capital flows including foreign investment. Turkey and Pakistan both rely significantly on borrowing from outside sources, so fluctuations in interest rates have the potential to quickly alter how investors behave and stock market performance. Following on, the moderate error

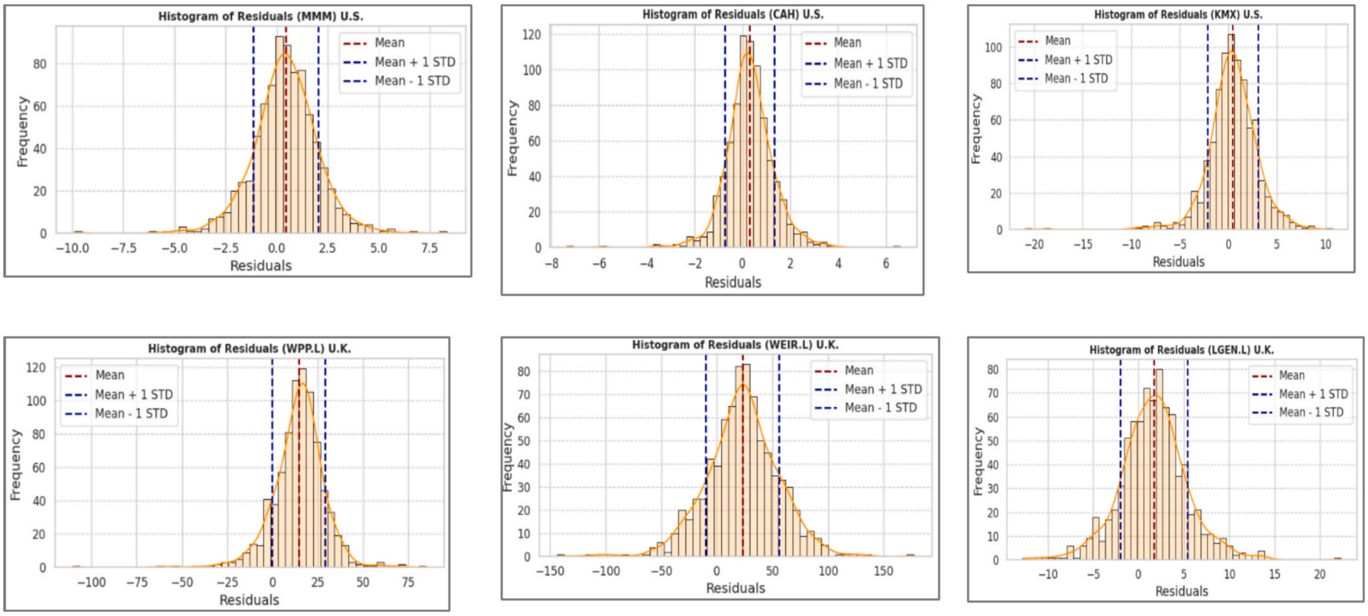

Fig. 13. Histogram of residuals for selected stocks from the U.S. and U.K. markets.

values are observed with the unemployment rate i.e. (MAE: 0.01135 and 0.00967), but these are still somewhat higher than those obtained from interest rates but less than those obtained from GDP or inflation. Overall, results in these two emerging as well as highly volatile markets show the potential of the proposed MEIG model in exhibiting very minimal error values. Moreover, the actual and predicted prices of the MEIG model are also plotted in this case as shown in Fig. 11. It is observed from Fig. 11 that forecasted prices are closely aligned with the actual prices of stocks in both Turkey and Pakistan.

4.8. MEIG performance on graph NODES

In addition to reporting cumulative findings of the MEIG model, this study also assesses the model in terms of its error on each node of a graph i.e. individual stocks. One of the major advantages of MEIG (a graph-based model) is simultaneously learning cross-market interactions i.e. stocks of one market/country with stocks of another market/country) as well as within-market interactions among stocks. In addition to this, these graph models have the advantage of predicting the future stock prices of all stocks present on each node. This flexibility and topological structure of the graph model makes the model more reliable to access and portray the results of each stock. The results of some stocks from each market are provided in Tables 10–14. More precisely, the results of the stocks of U.K. are provided in Table 10, and it is observed the proposed MEIG model is showing minimal error values, especially with NWG.L, BARC.L, and LLOY.L which is about 0.00179, 0.00823 and 0.00403 respectively. Likewise, the results of individual stocks of the U.S. stock market (SP500) are provided in Table 11, and it is observed that the proposed MEIG shows extremely minimal errors with stock symbols AIG which is about 0.00092. Similarly, Table 12 shows the individual stock results of Pakistan, and it is observed that in most cases, the values of MAE for KSE stocks are less in comparison with markets of the U.S. and U.K. Following on, the results of the proposed MEIG model are provided for stocks belonging to the Chinese stock market. It is observed from Table 13 that MAE error values are minimal, especially for some stocks e.g. 601318.SS, 601669.SS, and 600104.SS exhibit the lowest MSE values of 6.00E-05, 4.00E-05, and 3.00E-05 indicating the potential of MEIG. Similar to prior stock markets, the values of error for stocks of China are also minimal, however in comparison with other stock markets, the errors are a little bit higher, particularly in the case of Pakistan. In the last, the stock-wise values of Turkey's stock market are provided in Table 14.

4.9. Validating MEIG on large future horizons

To further demonstrate and analyze the performance of MEIG in terms of how well it makes predictions when larger future horizons are required, detailed experimentation on all five stock markets with different input sequence lengths has been carried out as ablation studies. Tables 15–19 show the results of different pairs of markets such as "U.S. and U.K.", "P.K. and Turkey", "U.S. and China", "U.K. and Turkey", and "U.S. and P.K." with different input sequence length and future horizon greater than 1.

The results show that the proposed MEIG shows good results even on forecasting 2-day ahead and 3-day ahead. The MEIG model is strong in tracking each short- and medium-term fluctuations in markets, as evidenced by its low error values even despite difficulties in forecasting stock prices across prolonged horizons. For instance, in Table 15, with input sequence 3, the MAE error value is 0.01366 for a forecast horizon greater than one which is quite minimal in the case of PK and Turkey cross-market learning. Likewise, with forecast horizon 3, and input sequence 5, the error value is 0.01391 with cross-market connections among U.S. and U.K. stocks. Subsequently, it is observed that in the results of U.S. and China cross-market learning with forecast horizon 3, the error is a little bit higher i.e., 0.02848 in comparison with other stock markets. In the last, the results of the U.S. and P.K. are also promising with the lowest MAE of 0.01071 with a forecasting horizon of 3 while the minimum error value is 0.01119 with U.S. and U.K. respectively. The rationale for improved results is the consideration of inter-intra events in addition to inter-intra graphs as well as macroeconomic factors. All these variables make the MEIG model more complete and fully aware interconnected financial system, hence leading to the improved and precise forecasting of stock prices. Fig. 12 shows scatter plots of predicted stock prices for several stock symbols in different markets, Fig. 13 shows residual plots, while actual and predicted prices over large future horizons as line plots are depicted in Fig. 14.

4.10. Comparison of proposed MEIG with baseline methods

The performance of the MEIG model is validated against the traditional baseline methods for stock price forecasting including Support Vector Regression (SVR), Random Forest (RF) regression, Long Short-

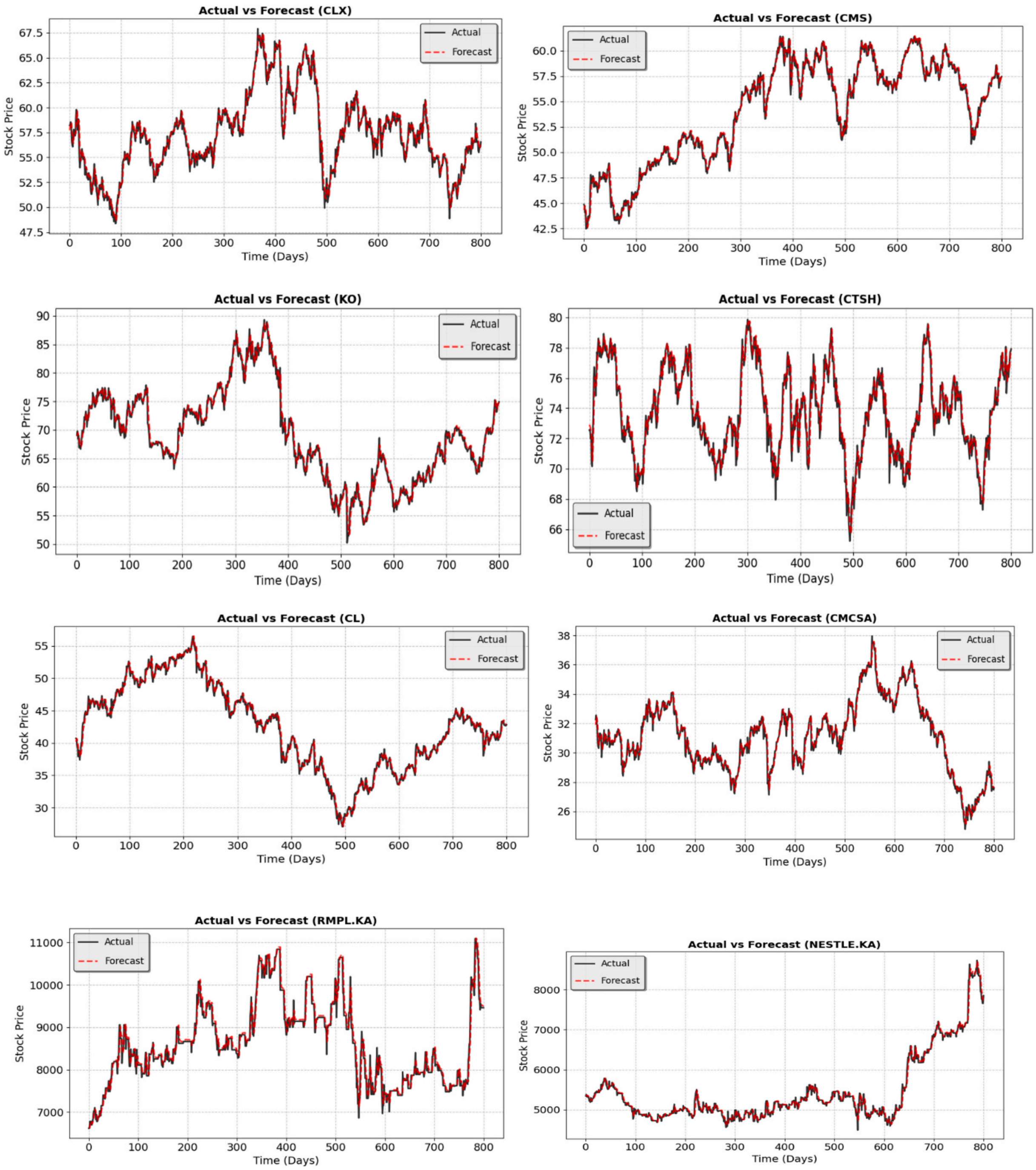

Fig. 14. Actual and forecasted prices over large future horizons of forecasting (i.e. 3 day ahead) by modeling cross-market economies (U.S and Pakistan).

Term Memory (LSTM), and Bidirectional LSTM (BiLSTM). The reason for choosing these models comes up from their widespread application in financial forecasting and the variety of underlying approaches. Comparing our MEIG model to these existing methods for stock price forecasting indicates the potential benefits of using cross-market graph-based architectures to capture complicated connections in financial data. Fig. 15 shows the results of different methods in comparison with MEIG across different stocks. More precisely, from each stock market index, top volatile stocks based on their standard deviation of returns have been selected to be compared with MEIG. The results indicate that the proposed MEIG model obtains good and lowest error values in comparison to traditional ML and DL methods. For instance, the MEIG model had an MAE of 0.00827, which was considerably less than the MAE values for SVR (0.2120), RF (0.38983), LSTM (0.03250), and BiLSTM (0.02764) in case of "ENPG" stock from U.S. market. The lower MAE suggests that MEIG's forecasts are more like actual stock prices. The rationale behind this is that it works by modeling each stock as a node in a graph, enabling the model to acquire knowledge of the interactions and interconnections between all stocks i.e. within markets and cross markets. This holistic strategy improves prediction accuracy by making use of the stock market's interconnectedness. Each method that is utilized for comparison has its own strengths and limitations. For instance, SVR shows good performance in high-dimensional spaces but faces challenges when framed for non-linear tasks. Likewise, the RF regression model shows a lack of performance with noisy data. LSTM and BiLSTM are good at capturing temporal information, however, they are limited in terms of learning stock-to-stock relationships. Additionally, models like LSTM, BiLSTM, SVR, and RF work on each stock

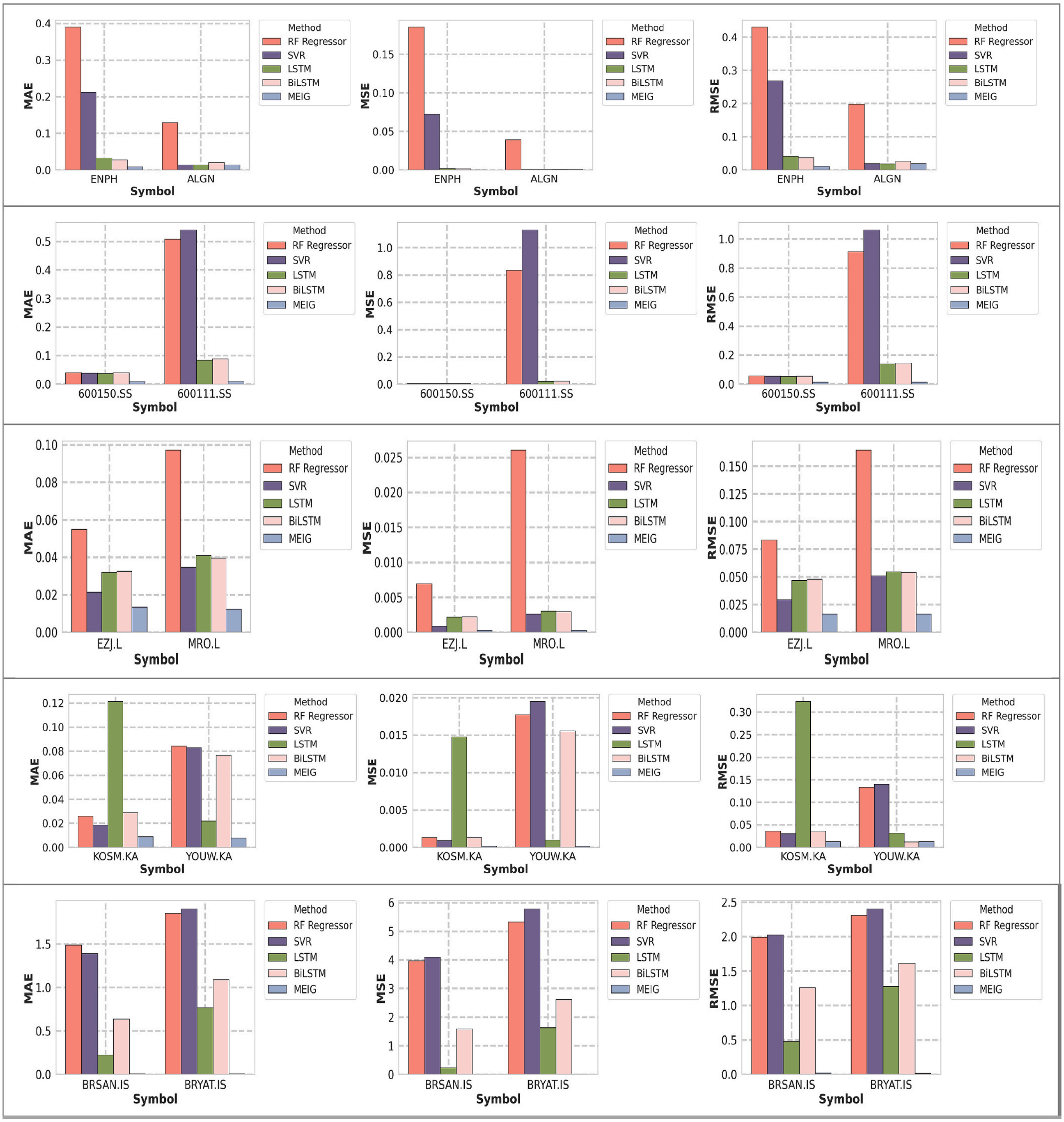

Fig. 15. Comparative Analysis of Proposed MEIG Inter-Intra Graph Model with baseline methods on stocks of different markets.

independently. This requires training a different model on every stock, resulting in substantial computational costs. These models do not account for stock connections, for example, cross-market correlations and inter-intra events-based correlations. Hence, these limitations have been addressed in the MEIG model which is an improved version of the traditional GNN model in which instead of focusing on a single stock market, the relationships of stocks across borders and with other markets have been modeled. In addition to that, the intra-inter events impacts as well as macroeconomic factors are also considered, thus creating a comprehensive financial interconnected system. In addition to these, the MEIG supports simultaneous training of stocks on graph nodes thus reducing training overhead as well as also being able to learn the cross-market and within-market interdependencies among stocks.

4.11. Discussions and implications

Stock price forecasting is one of the most popular research topics among the researchers of finance. Currently, AI approaches have progressed from traditional machine learning methods to emerging sophisticated deep learning methods, with graph neural networks being utilized most recently by different researchers. The primary distinction between the traditional and deep learning models to frame the problem of stock price forecasting is their modeling of stock-to-stock relationships. Traditional methods overlook such relationships; however, they have an important impact on fluctuating stock prices (Wang et al., 2111). The primary cause for observing them as one unit (i.e. without considering stock-to-stock connections) is the assumption that stocks are interdependent. With the emergence and applications of GNNs in the finance domain, stock-to-stock correlations have been modeled into the GNN by the latest studies, regardless of the conventional assumptions. Most of the studies exploited GNN models by framing the problem as stock movement i.e. classifying the trend of stock prices into two classes e.g., “upward trend” and “downward”. This is a simple problem, but it does not predict how much the future stock price will rise. As a result, forecasting that is precise and explicit is more essential than stock market movement, but it is difficult owing to the chaotic and volatile nature of the stock market, intra-inter events, and inter-intra macroeconomics. Furthermore, presently latest studies on graph models for stock price forecasting rely primarily on intra-stock markets when constructing stock interactions for stock price forecasting, ignoring inter-stock market associations between stocks. Nevertheless, globalization has made financial markets more integrated, because changes in one country’s economy or policies may affect stock values in other countries (Shahzad et al., 2022).

To address such issues and make the GNN model portray the more comprehensive financial interconnected systems of the stock market, this study presents a MEIG model to build an intra-inter graph (i.e. both with and within cross-border relationships) with their corresponding inter-intra events. In addition, macroeconomics factors are also modeled into intra-graphs as node features turning the problem into a multivariate time series on each node of MEIG. Moreover, the Cross-Graph Attention Layer (CGAT) is also proposed to weigh the importance of stock connection within their respective intra-market and inter-market networks. This underlines the importance of inter-intra-connections between stock markets for forecasting stock prices. The results have been validated on five different stock markets namely SP500 (United States), SSE50 (China), KSE-50 (Pakistan), BIST (Turkey), and FTSE (United Kingdom). Different experimentation setups have been designed to study the impact of cross-market correlations in stock price forecasting between different economies such as between developed economies, between developed to emerging economies, between emerging to emerging economies, and between superpower economies. In addition, the impact of event sentiment has also been involved by modeling them into their inter-intra graphs. Different types of tweets from Twitter against these events have been collected. It is observed from the results that MEIG models show good results in learning cross-market interactions. Moreover, the experimentation has also been carried out with large future horizons and comparison has also been done against standalone intra-graphs, and it is observed that the proposed MEIG model shows good results.

The implications of this research include that the proposed MEIG model provides investors with a more nuanced tool for forecasting stock prices, especially in today’s globally interconnected markets. In the GNN model of an interconnected system of intra-inter stocks, the fusion of macroeconomic indicators and event-driven sentiment allows for more accurate forecasting, and thus for more informed investment decisions. The proposed methodology takes advantage of inter-market connections by creating a global network connecting stocks across economies. These links enable the model to reflect global financial patterns, cross-border capital flows, and how economic circumstances or events (e.g., political events or natural disasters) in one country affect stock prices in another. This has obvious impacts on investors, portfolio managers, and businesses seeking to improve their portfolio management practices by using international market data and sentiment analysis.

5. Conclusion

Stock price forecasting has always been a challenging endeavor in finance due to the chaotic and volatile nature of stock markets and serves a critical part in financial planning, risk management, and investing strategies. Existing models usually predict stock prices inside a single stock market, using localized graphs to illustrate relationships under a single country’s market. To address such issues, an MEIG model is proposed in this research leveraging the cross-market interdependencies to model by also involving cross-market macroeconomics as well as events. The proposed MEIG builds inter-intra graphs and represents multivariate time series on nodes by integration of macroeconomic indicators (GDP, inflation rates, unemployment, etc.) and local/global event sentiment (such as political elections or protests) into the forecasting framework. In addition, the Cross-Graph Attention Layer (CGAT) is also proposed to weigh the importance of stock connection within their respective intra-market and inter-market networks. The MEIG model has been evaluated on five distinct stock markets, and the impact of cross-market correlations on stock price forecasting was investigated in various types of economies. For example, between developed, developing, and superpower economies. The results of the proposed MEIG models show improved performance in terms of achieving the lowest error values collectively, as well as individually on each node. The macroeconomics and inter-intra event sentiments model the comprehensive view of the country, thus enhancing forecasting accuracy. Future work includes the exploration of fundamental and technical indicators-based ratios in addition to adapting the MEIG to evolving inter-intra graph depending upon the time-varying correlations variations among stocks of cross-border markets.

CRediT authorship contribution statement

Maryam Bukhari: Software, Methodology, Formal analysis, Data curation, Visualization, Writing – original draft. **Muazzam Maqsood:** Methodology, Conceptualization, Investigation, Writing – review & editing. **Asma Sattar:** Formal analysis, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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