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CASE STUDIES

Machine learning in supply chain: prediction of real-time e-order arrivals using ANFIS

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Abstract Accurate demand forecasting throughout the multi-channel supply chain (SC) enhances the managers' decision-making capability in operational, tactical, and strategic aspects. However, the problem is that earlier publications about the real-time prediction of e-commerce order arrivals in the SC show some inadequacies. According to a systematic review from Tsolaki (ICT Express, 2022. https://doi.org/10.1016/j.icte.2022.02.001) who integrate logistics and machine learning (ML) methods in the past ten years, there are very few studies that focus on arrival time prediction like this study does, and none of them uses an adaptive neuro-fuzzy inference system (ANFIS) framework to predict e-order arrivals. Besides, (Policarpo in Comput Sci Rev 41:100414, 2021) review the existing publications that integrate e-commerce and ML techniques in the past five years; they reveal that previous studies pay heavier attentions to e-commerce initiative goals such as purchase and repurchase predictions, and none of them focuses on predicting e-order arrivals like this study does. Previous scholars investigate SC orders and prediction issues in a broader space, while this study attempts to predict hour-to-hour, actual-time order arrivals. Thus, this study presents a new data-empowered forecasting method to fill these research gaps. The motivation of this study is to build a method for predicting real-time e-orders arrivals in distribution hubs, enabling third-party logistics providers to handle the hourly-based e-order arrival rates more efficiently. This study tries to find the solution for the problem by developing a new ML forecasting method by integrating time-series data features and ANFIS, which has been proven to significantly reduce the issues' computational complexity. This study creates a four-phase operation model to enable managers to adopt the suggested framework, and develops a systematized forecasting model to cross-confirm the framework's outcomes. This study employs a descriptive case study and shows a satisfactory degree of precision of the suggested ML method in predicting the actual e-order arrivals in three e-retailers at three-hour cycle times. The findings reveal that the real-time forecasting is significant to boost the values of e-order arrivals in every day business operations. The novelty of this study lies on its novel contribution and purpose to build a method for predicting real-time e-orders arrivals in distribution hubs, enabling third-party logistics providers to handle the hourly-based e-order arrival rates more efficiently; and to develop a new ML forecasting method by integrating ANFIS and time-series data features.

Keywords Machine learning · E-commerce · Supply chain management · Third-party logistics · Real-time demand prediction

JEL Classification C45

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1 Introduction

Effective organisation of the all-inclusive e-commerce order (e-order) fulfilment practice is significant to third-party logistics providers (3PLPs) and e-retailers, and because the frequency and timeliness of order fulfilment are significant accomplishment measures in 3PLP (Baruffaldi et al. 2020; Li and Jia 2019) and e-retailers (Zhang et al. 2019; Jiang and Li 2021). 3PLPs should manage daily-based e-orders demanded by final customers through the numerous marketing channels of e-retailers to attain a high standard of service in current industry dynamics and tighter customers' demands. Outsourcing the whole order fulfilment processes to 3PLPs is a usual practice of e-retailers. 3PLPs form strategic affiliation with numerous e-retailers manage a multitude of e-orders from diverse e-retailers to develop their e-commerce logistics (e-logistics) industry. Allocating an exclusive storage zone for every retailer's products is a regular procedure of a 3PLP fulfilment hub. Based on this, the order fulfilment processes of the selected area are triggered by receiving orders from a specific retailer (see Fig. 1). Figure 1 displays seven steps in typical e-order fulfilment operation: (1) Online consumers buy products from many e-sales boards; (2) E-retailers list their goods line up on numerous e-sales boards to expand sales and brand publicity, (3) Assume the 3PLP is ini alliance with 3 retailers, (4) E-retailers get e-orders from final customers and convey each order details to 3PLP regularly to fulfill e-orders, (5) The 3PLPs fulfill the orders appropriately, (6) Stock of every retailer is saved individually in different zone, (7) Resources (e.g., order pickers) should be assigned to various zones based on the dynamic, actual-time order arrival rate in every zone. This typical e-order fulfilment faces current issues in the dynamic resources allocation procedure in e-commerce, i.e., how will the existing resources be compliantly assigned to every area to fulfill orders? There are three causes of the decision-making complexity in this subject: (1) e-order arrivals in every e-retailer is extremely varied., the peak times can fluctuate or intersect among the e-retailers during a day, (2) the desion-making about resources re-allocation must be in timely basis (e.g. every hour/2-h), based on the actual time e-order arrival rates, and (3) the absence of decision-making support. The poor or postponed decision makings can cause ineffective order management, backlogs of orders awaiting for handling, incapability to fulfill the delivery obligations, and low customer satisfaction and consumer buying experience.

3PLPs' problems in the e-commerce hub are caused by e-order fluctuation and the necessity of responsiveness in fulfilling orders. The final customers' order arrivals in every e-retailer are highly fluctuating and dynamic as final online customers can put e-orders on any occasion on their mobile phones or personal computers. Moreover, as the target consumers of every e-retailers are different from one another regarding, e.g., consumer' geographic location, the order arrival peak time(s) in various areas during the day differs and can overlap. Thus, to tackle the hourly based fast-shifting e-orders arrival rate brought on by many e-retailers, the 3PLPs should accurately and punctually redistribute resources, e.g., the order-picking utensils and workers, to every area in increasing the output rate through the entire areas of the fulfilment hub. As these resources should be distributed to every area vigorously, service providers search for reliable predictive techniques in forecasting real-time e-order arrivals.

Previous studies prove that ML techniques are effective in delivering actual-time predictions for practical data-focused decision-makings in the SC and offers the scholars, managers, and decision-makers recommendations about the effective SC management to support a more productive and sustainable SCs (Akbari and Do 2021; Jamwal et al. 2021; Sharma et al. 2020). Besides, scholars such as Kamble et al. (2021), Hamdan et al. (2021), and Hamdan et al. (2022) use ML techniques to predict the adoption of technology in the SCs of various industries and find that ML techniques provide more accurate predictions of influential determinants than other methods such as structural equation modeling.

The study integrates the advance predicting method using ANFIS with the time sequence features of e-order arrival statistics, i.e., the traits of the moving averages (MV) of earlier times, momentum (MM) of data variations, and autoregression (RG). These research methods demonstrate the nearly-real-time e-order arrival rate of every e-retailer. Thus, several ANFIS-RG-MM-MV-empowered predictive frameworks are created based on the entire sum of e-retailers affiliated with 3PLP. Every framework is tested and trained with an accurate and unique dataset of past order arrivals of an e-retailer. An examination involving comparisons is directed to verify the functioning of the suggested method in forecasting e-order arrival in every area of distribution hubs. To summarise, the study proposes the construction of:

- A data-empowered machine learning forecasting method using the information provided by e-retailers down the chain to predict the nearly-real-time e-order arrival of every single resource,
- An applied multi-phase operation model for business leaders to create, verify and implement the forecasting framework according to their actual operative data, and
- A systematised estimation model for a pairwise dimension of the suggested ANFIS-empowered framework's forecast accuracy relating to an autoregressive integrated moving average (ARIMA) framework.

Those constructions fundamentally emphasise the study's contributions to practical and theoretical aspects. Practically, the study proposes a machine learning forecasting method that combines three features, i.e., RG, MM, and MV of time sequence data. The framework is simplified to cover more extensive implementations in any vertical business for improved operative decision-making with great prediction precision. This paper presents a four-phase operation framework in a systematised estimation model for facilitating leaders to employ the framework in

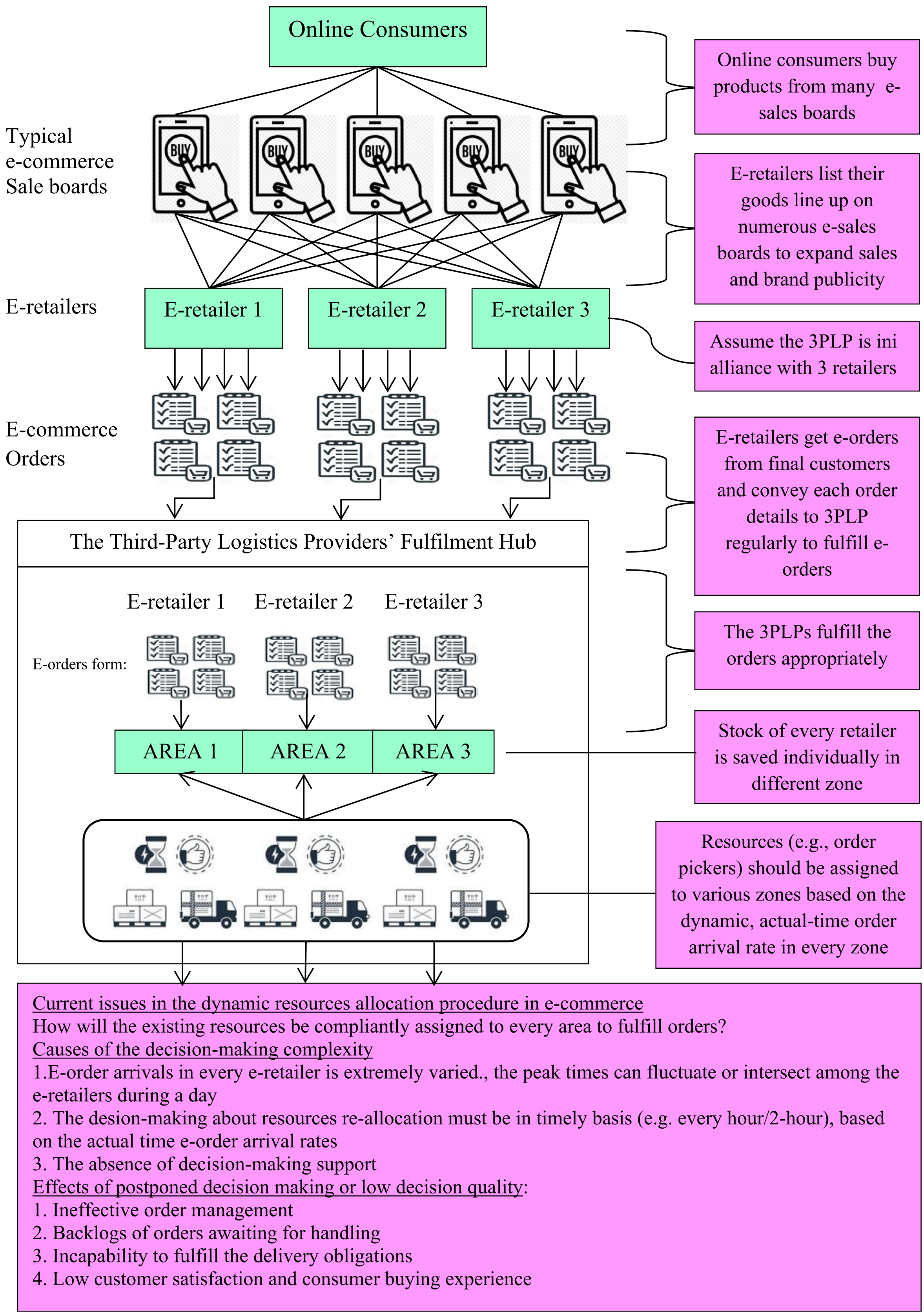

Fig. 1 Typical e-order fulfilment operation and its triggering blockages

their actual industry environment and analytically gauge their ANFIS frameworks' forecast accuracy.

Theoretically, the paper subscribes to a broader research area, which concentrates overtly on the bottlenecks and operative subjects in managing e-business. Previous scholars investigated supply-chain demand, a predictive issue on a broader space, especially in handling the bullwhip effect. The earlier publication demonstrates wholesale distribution processes by incorporating two artificial neural systems applied to predict retailers' demands (Bottani et al. 2019); it also uses genetic algorithm to identify vital predictors of the SC network performance (Chen and Chen 2022). In existing studies, forecast of hourly based, real-time order arrival remains scarce. As contrasted to earlier publications in SC issues, this study' methodology overpowers the limitations of broader time lags, e.g., monthly or weekly, for managing daily operations. The E-commerce age makes e-order arrivals in the viewpoint of 3PLPs more recurrent and dynamic than the traditional, large-scale, frequently appeared logistics demands. Due to e-order arrival's characteristics, making demand forecast in a much nearer period has become more crucial to create more significant decision support and to help leaders in everyday operative decision-making processes.

However, earlier publications about the real-time prediction of e-commerce order arrivals in the SC show some inadequacies. First, although previous studies have proven that ML techniques, especially ANFIS, are effective in delivering actual-time predictions for practical data-focused decision-makings in the SC (Mubarak et al. 2022; Rožanec et al. 2021; Kumar et al. 2020; Lima-Junior and Carpinetti 2020; Okwu and Tartibu 2020; Tzalavra et al. 2022), very few studies have used ANFIS in predicting the e-order arrival. According to a systematic review from Tsolaki et al. (2022) regarding journal and conference publications in the past ten years, there are only 12 papers focusing on arrival time prediction in the SC and logistics fields using machine learning techniques and none of which uses ANFIS framework to predict order arrivals like in this study. Second, among the extant literature focusing on the use of ML in e-commerce, studies that predict e-order arrival are scarce. According to a recent review from Policarpo et al. (2021), the existing publications that integrate e-commerce and machine learning in the past five years and reveal that these studies focus on e-commerce initiative goals such as purchase and repurchase predictions and none of them concentrates on e-order arrivals prediction like in this study. Consequently, the study tries to fill these literature gaps and provides understandings for business leaders and academicians to promote big data from the cloud to enhance the decision-making process in B2C and B2B e-business settings via the equipment of ML systems.

Based on the problems and motivations above, the novel contribution and purpose of this paper are: (1) to build a method for predicting real-time e-orders arrivals in distribution hubs, enabling third-party logistics providers to handle the hourly-based e-order arrival rates more efficiently; and (2) to develop a new ML forecasting method by integrating ANFIS and time-series data features. Specifically, this study attempts to answer the following research questions (RQs):

- RQ1: What is the most suitable framework structure for every dataset of e-retailers' order arrivals used in this study?
- RQ2: How does forecasting accurateness perform in the various concepts and frameworks of this study?
- RQ3: How does the forecasting accurateness differ between ARIMA and ANFIS methods?

To answer these RQs, this study uses: (a) an ML method incorporating time sequence data features and prediction of e-order arrivals, and (b) a prediction method with a case illustration that is explained systematically in Part 3 of this paper.

The remainder of the study is presented in the following sections. Part 2 describes a literature review of the contemporary studies and models associated with the subject. The suggested research method for the e-order arrival framework is displayed in Part 3, while the discussion of the framework implementation supported by a case illustration is presented in Part 4. The study's findings are described in Part 5. Last, Part 6 concludes this research and guides future studies.

2 Related works

2.1 ML implementation in the SC

The effects of e-commerce on SC management, warehousing, and logistics have been broadly reviewed in the latest years. However, studies related to operative decision support to handle e-fulfilment processes in warehouse remains scarce (Nguyen et al. 2018). From the operative viewpoint, order sorting, zoning, and batching are still unresolved issues, particularly in the existing e-business environment, although these are dynamic research areas with numerous related studies generated (Boysen et al. 2018). Other scholars accentuated the necessity to enhance the functioning of the last-mile logistics regarding the efficiency of resources and services because this development will result in optimistic social effects (Lim et al. 2018).

Some scholars have used non-ML method in the SC, such as fuzzy best–worst method (Sumarliah 2021; Sumarliah et al. 2021c), structural equation modeling (Sumarliah et al. 2021d), and conceptual approach (Sumarliah et al.

2020, 2021a, 2021e). However, there are previous studies employing ML techniques in the SC to get better results. For example, Akbari and Do (2021) examine the publications focusing on the applications of ML in SC management and logistics listed major databases in the past 25 years (1994–2019). They find 110 publications related to this subject, which consist of nine literature reviews, 53.8 per cent of publications were closely clustered on transportation and manufacturing industries, and 54.7 per cent were centred on mathematical models and simulations. Neural network is applied in 22 papers as their exclusive algorithms. Finally, the main focuses of the current literature are on prediction and optimization. Jamwal et al. (2021) review the existing publications using bibliometric assessment and propose a framework that underlines how ML methods can be implemented to manage sustainable manufacturing challenges in manufacturing stage of the SC.

Kamble et al. (2021), Hamdan et al. (2021), and Hamdan et al. (2022) use ML techniques to predict the adoption of blockchain technology in the SCs of various industries to overcome the shortcoming of simpler technique such as structural equation modeling used by other scholars (e.g., Sumarliah et al. 2022b). They develop extrapolative decision support systems employing Bayesian network examinations; the results suggests that Bayesian framework contains substantial predictors that managers can apply to predict the high likelihood of adopting blockchain in the SC of their firms.

Sharma et al. (2020) provide a methodical review of ML usages in agriculture SC. They studied 93 publications based upon the uses of various ML procedures in many stages of the agricultural SC. They highlight how ML methods can be useful for the more sustainable SC. They develop ML usage model for enabling sustainability in the SC; this model discovers the function of ML systems in delivering actual-time diagnostic perceptions for practical data-focused decision-makings in the SC and offers the scholars, managers, and decision-makers recommendations about the effective SC management to support a more productive and sustainable agriculture SCs.

Shaikh et al. (2022) identify influential predictors of ML-enabled demand prediction and find that it supports in improving consumer engagement, examining shoppers' behaviours and product tracking along the SC points from sourcing point to final consumer point. Bisheh et al. (2022) use an ML technique, i.e., transfer recurrent neural network (RNN) to propose a novel method for seeing consumers' differentiation in a combined allocation-location and inventory management framework. Bhargava et al. (2022) use artificial intelligence to study the particular indicators of scheduling in logistics such as actual-time supervising and predictive preservation of logistic transportation tools for effective operations.

2.2 ML implementation in e-commerce

The multi-channel retailing and e-commerce era has transformed customer buying practice (Sumarliah et al. 2022a). Marketing networks have been growing, from physical shops to social media platform and online shopping websites (Sumarliah et al. 2021b); it has led to immense prospects and problems for e-retailers and 3PLPs regarding the fulfilment of an abundance of time-critical consumer demands. The flourishing of e-retail performances in SC management has dramatically affected the latest e-logistics operative flow (Zhu and Liu 2021). E-fulfilment hubs, distribution hubs, and warehouses operate for transitional handling and storage of products in an e-logistics setting. Final customers highly need these components to tackle e-orders correctly and highly fulfilled (MacCarthy et al. 2019). Nevertheless, e-retailers and 3PLPs meet special conditions for e-order fulfilment, e.g., low quantity of e-orders, strict distribution timetables and fluctuating assignments, causing consequent problems for traditional stores to fulfil those conditions (Boysen et al. 2018). The extremely time-sensitive order fulfilment practice essentially pressures 3PLPs to lessen the volume of order accumulation and, consecutively, guarantee that 'today' or 'tomorrow' delivery agreement can be fulfilled (Klapp et al. 2018). However, previous publications which focus on the use of ML in e-commerce are very few. For example, Shaikh et al. (2022) analyze the key predictors of ML implementation in e-commerce and find that ML is valuable for tracking products along the SC (from sourcing point to consumer point), supporting the analysis of shoppers' behaviors, and improving consumers' engagement.

2.3 ML implementation in other fields

ML has also been used for prediction in various fields other than e-commerce and SC management. For example, Li et al. (2022) employ an ML technique, i.e., deep learning (DL) innovation, and propose an IoT security risk framework integrated with edge computing (EC) system. They reveal that DL and EC technologies have significant effects in improving the decision capability of the IoT security risk framework and enhance the effectiveness of web area governance. Wu and Tong (2021) try to answer the loan problems in agrarian companies using DL and neural network framework and reveal that the proposed model significantly enhance the firms' general loan capability and efficiently assess business barriers. Singh et al. (2022) examine ML techniques, i.e., non-linear and linear Bayesian regression approaches to predict softwares' defects and reveal that Bayesian network performs better than linear regression and other ML techniques.

Scholars Malsa et al. (2021) uses an ML technique, i.e., Long Short-Term Memory (LSTM) framework for predicting cryptocurrency with Root Mean Squared Error (RMSE) to measure framework effectiveness. They find LSTM as the most useful framework to estimate precise rates for the prospect; thus, investors can invest and get profits. Gao et al. (2021) apply ML technique such as neural network innovation to control automatically administered diesel engine injection and reveal that the neural network framework can control injections that are managed by machine more quickly and effectively. Finally, Amalnick et al. (2020) employ ML techniques, i.e., data mining and neural network technologies to present an intelligent algorithm to predict customers' demand in pharmaceutical businesses. They reveal that this model provides the more accurate forecasting and a higher reliability of the predicted values in the test.

2.4 ANFIS implementation for prediction

Inspired by the reality that logistics functioning is considered a vital factor influencing practical decision support and e-order fulfilment for handling operative issues in fulfilment hubs is vital. The study tries to fill the literature gap by demonstrating and predicting e-order arrivals in fulfilment hubs. E-order arrival is a valuable forecast topic due to its essential for daily decision-making processes, e.g., real-time distribution of active supplies in various warehouses' areas based on e-order arrivals' underlying forces (Dauod and Won 2021; D'Haen et al. 2022). This research method incorporates time-series features with ANFIS construction. The ANFIS method is adopted in demonstrating e-order arrivals because it is a broadly acknowledged and implemented instrument for neural network development and has been applied in handling issues in various businesses. Researchers such as Qamber (2022) used ANFIS to predict energy usage; Adnan et al. (2021) applied ANFIS to estimate agricultural water supplies. ANFIS is also broadly adopted to predict stock market indexes and prices (Alenezy et al. 2021; Hussain et al. 2022; Kumar Chandar 2019).

Regarding SC management, scholars such as Mubarak et al. (2022) and Rožanec et al. (2021) used ANFIS for demand or sales prediction; Kumar et al. (2020) for bullwhip effect mitigation; Lima-Junior and Carpinetti (2020) for SC performance assessment; and Okwu and Tartibu (2020) for supply partner selection. In brief, the self-learning capability and the mixture of advantages of neuro-fuzzy networks make ANFIS surpass different neuro-fuzzy approaches in successfully, adaptatively, and flexibly answering non-linear operational issues (Tzalavra et al. 2022). Singh et al. (2021) use ANFIS to predict traffic noise level in roads, while Mabrook et al. (2020) employ ANFIS algorithm to detect the optimal and accurate free music channels, and Senthilselvi et al.(2021) use ANFIS to predict noisy pixel patterns to remove impulse noise from the image. All these scholars find that ANFIS performs better than other prediction methods.

Conventional time-sequence forecasting techniques cannot tackle the complexity of nonlinear association in a big dataset (Hussain et al. 2022). Many current methods cannot handle numerous extents of a dataset because of which the computational complexity intensifies alongside the growing dimension of datasets (Hussain et al. 2022). Nowadays, neuro fuzzy system is well-known in studies because of its simplicity in treating the issues of data complexity and imprecision (Senthilselvi et al. 2021). ANFIS has been empirically proven to have superior performance than other methods such as fuzzy inference system through optimization procedure (Senthilselvi et al. 2021), and other neuro-fuzzy approaches through self-learning capability and excellences in answering non-linear operational issues (Tzalavra et al. 2022). ANFIS significantly reduces the issue's computational complexity (Asghar and Liu 2018). The fuzzy systems' computational complexity relies on the quantity of "If–Then" policies. The quantity of fuzzy policies in a traditional fuzzy policy centre method cis computed as 'nm', where 'n' is the quantity of relationship functions (RFs) allocated to every input and 'm' is the quantity of input constructs. Employing this formulation, the quantity of fuzzy policies will be big and cause higher complexity and wasteful of time in decision makings; even the scheme can stop for the higher quantity of fuzzy policies. ANFIS is special due to its capability to robotically generate the fuzzy policies through the assessment of the output-input training datasets; thus, it largely lessens the problems' computational complexity (Asghar and Liu 2018). Besides, ANFIS benefits the learning capability of artificial neural networks; it instructs the RFs of input constructs with least square procedure and posterior transmission slope decline procedure (Asghar and Liu 2018). The instructed policies minimalize the RMSE and enable the network to precisely generate the outputs for particular rates of inputs.

Thus, this study demonstrates a united ANFIS-empowered forecast framework to accurately predict e-order arrivals in fulfilment hubs and support operative decision-making practice in fulfilment hubs, particularly in handling active resource distribution issue, with a reduction of dependence on human experience and knowledge.

3 Materials and methods

3.1 A machine learning method incorporating time sequence data features and prediction of e-order arrivals

This part explains the machine learning method to predict e-order arrivals using a case illustration for easy description.

First, this study introduces the determinant of input constructs, i.e., RG, MM, and MV; then, the methodological aspect of ANFIS frameworks.

3.1.1 Case overview

This paper involves a case firm that has worked in the e-logistics segment for the past decade (2010–2020). The sum of affiliated downstream retailers in this case firm has been rising progressively, but three e-retailers primarily form most e-orders. Thus, the framework construction procedure for predicting e-order arrivals is assumed for the three separate e-retailers. For operative assessments of every single prediction framework's forecast implementation, the study develops two concepts with a sum of eight ANFIS-empowered prediction frameworks. Figure 2 presents the background and primary foundation of the construction of two concepts, i.e., Concept A and B. It is evident from Fig. 2 that after the first four steps of typical e-order fulfilment operation as mentioned in Fig. 1, e-retailers obtain e-orders and send the detail of every single e-order to 3PLP to be fulfilled. Then concept A and B are developed. First, concept A is established to discretely predict every e-retailer's e-order arrival, using 3 ANFIS frameworks for predicting each e-retailer's e-order arrival. ANFIS framework 1, for example, forecasted e-order arrival of e-retailer 1 for the coming cycle time $\tau+1$. Then, the outputs of ANFIS framework 1, 2 and 3 are aggregated. The sum of forecasted e-order arrival of e-retailers 1, 2, and 3 signify the totality of e-order arrivals for the coming cycle time $\tau+1$. Second, concept B is developed to predict the total e-order arrival by combining e-order arrival from 3 e-retailers. E-order arrival of 3 e-retailers are combined to produce a sole ANFIS framework to predict combined e-order arrivals. Thus, the output of ANFIS framework is forecasted e-order arrival of combined e-retailers for the coming cycle time $\tau+1$.

Next, the study formulates the suggested prediction method based on the mentioned background.

3.1.2 RG, MM, and MV as determining factors

The paper proposes three kinds of constructs as the determining factors of the time-series- category e-order arrivals. Table 1 presents the rationalisation of choosing the three input constructs. The authors describe a set of procedures to properly incorporate those constructs in constructing the ANFIS-empowered framework to predict e-order arrivals. The procedure includes:

- Actual e-order arrivals from the earlier η_1 cycle times—presenting interval examination to find the order of the autoregressive interval constructs (RG) in every dataset
- The impulsiveness of e-order arrival between the earlier η_2 cycle times—describing the order of momentum (MM)
- η_3-cycle time simple moving average—pinpointing the number of times to move average (MV)
- Computing the RG, MM, and MV values of the entire data inspections in every dataset.

3.1.2.1 Real e-order arrivals of the earlier η_1 cycle times—presenting interval examination to find the RG order of every dataset This study formulates and estimates an RG framework using Eviews software to verify the proper quantity of interval times $\eta 1$, which is most suitable for the experimental dataset. This study firstly choose ten interval constructs for every dataset of e-retailer, i.e., $Qd(\tau-\eta)$ with $\eta=0, 1,..., 9$, for examination employing the least-squares technique. The null hypothesis must be rejected if the ρ-value is below the significance level of 0.05. Based on the case illustration, this study chooses 298 inspections to assess and examine the RG frameworks, which is the initial 2/3 (66.7%) of the sum of 448 inspections of e-order arrival obtained from an eight-week dataset in every three-hour lag. The interval examination findings correspondingly for the dataset of e-retailer 1, 2, 3 in concept A and the combined dataset in concept B.

Table 2 displays the examination findings of the RG(1) and RG(8) framework gauged by the determination coefficient (R^2) and RMSE. Table 2 exhibits that for the combined e-retailers' data, RG(8) presents lesser values of RMSE than RG(1), i.e., $33.4264<47.4878$, and higher values of R^2 than RG(1), i.e., $0.7315>0.4369$. It signifies that the RG(8) framework demonstrates better prediction of e-order arrival compared to RG(1). Table 2 summarises the most excellent RG framework for every dataset of e-retailer. Nevertheless, when the RG(8) framework is to be implemented, eight interval constructs are involved in the ANFIS framework. It can sternly enhance the calculation time and conditions and creating many if–then policies in the ANFIS framework's inference machine. Thus, considering those disadvantages in the ANFIS approach, the RG(1) framework is chosen over the RG(8) framework for e-retailer 1, 3 and the combined dataset. Parallel processes are carried out for e-retailer 2's dataset. In summary, the interval length (η_1) of every dataset is 1, signifying that one interval construct will be used as the input construct.

3.1.2.2 Impulsiveness of e-order arrivals between the earlier $\eta 2$ cycle times—describing the order of MM Over-complexity in the input construct sets should be avoided; thus, this case study uses one-order momentum, $MM(\tau)$. Hence, for the existing time τ, Eq. (1) is used to calculate the e-order arrival's one-order momentum as follows:

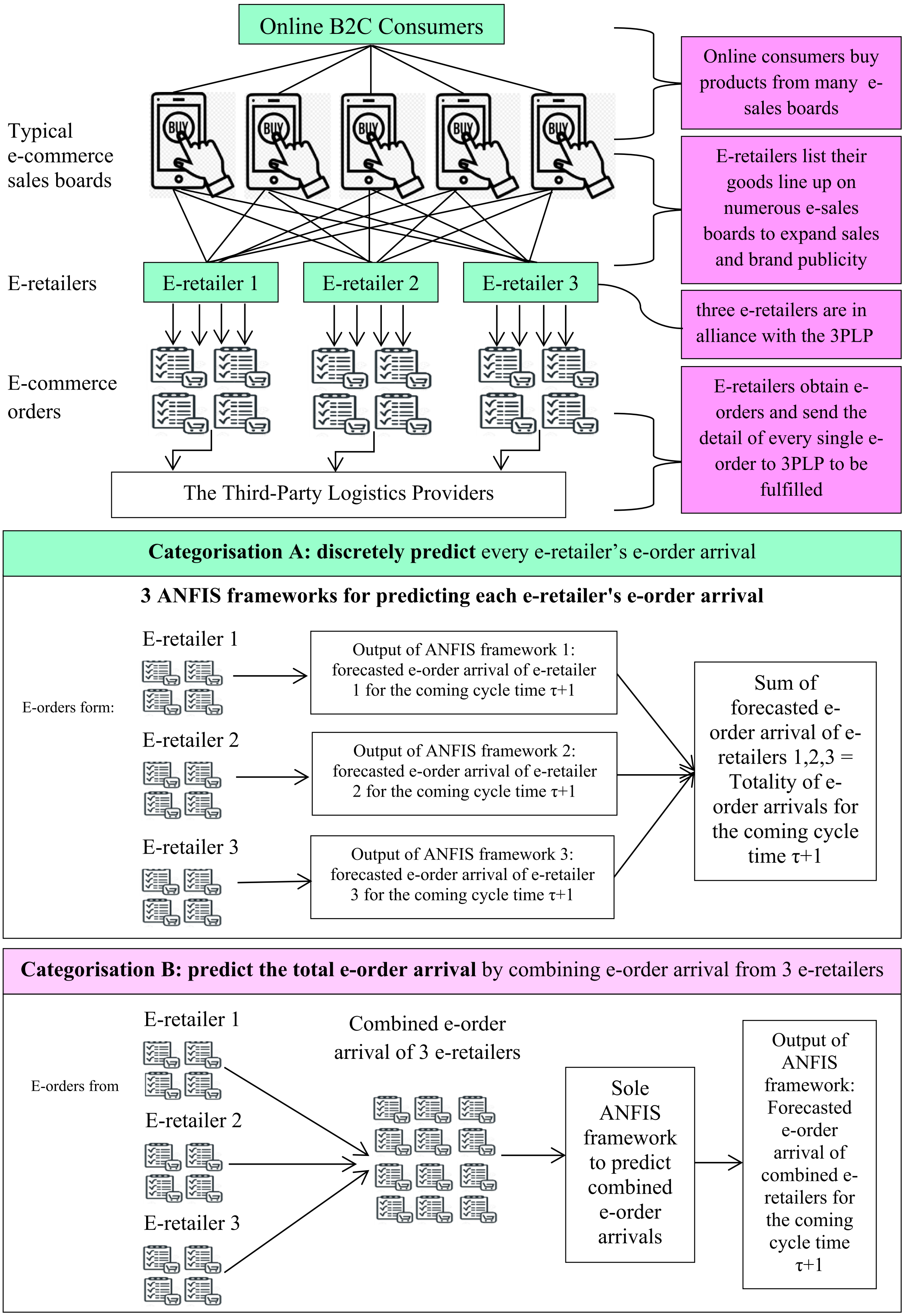

Fig. 2 Categorisation development for framework assessment

Table 1 Rationalisations of the constructs in the suggested ANFIS predictive frameworks

	Input constructs	Rationalisations
1	RG	In time-series data forecasting research, interval constructs, i.e., earlier performances, are the vital measures to predict the upcoming performance. Hence, the concrete e-order arrivals in the earlier η_1 cycle times, i.e., time τ, $\tau-1$, $\tau-2$,..., $\tau-\eta_1$, are significant forecasting measures to predict the e-order arrival performance of the coming cycle time $\tau+1$
2	MM	Earlier e-order arrivals (MM) impulsiveness is a significant measure for the time-sequence-enabled e-order arrivals' tendency. The measure has been employed to forecast inventory costs. It is a methodological measure for predicting stock costs. This paper also applies two-order and one-order MM because the input constructs are similar to this earlier study
3	MV	MV is an evident instrument that has been frequently presented as a forecast measure. A two-time and three-time MV are presented as the input constructs for the ANFIS prediction model

Table 2 Summary of interval examination findings for every single E-retailers dataset and the combined dataset

Concept	Datasets	Most excellent RG framework	R^2	RMSE
A	E-retailer 1	RG (1) framework*	0.3962	16.2763
		RG (8) framework	0.6604	12.3952
	E-retailer 2	RG (1) framework*	0.4064	16.8961
		RG (4) framework	0.2642	18.6944
	E-retailer 3	RG (1) framework*	0.4166	16.8351
		RG (8) framework	0.6807	12.5882
B	Combined the entire e-retailers' data	RG (1) framework*	0.4369	47.4878
		RG (8) framework	0.7315	33.4264

*Chosen interval length for every dataset

$$MM(\tau) = Q_d(\tau) - Q_d(\tau - 1) \tag{1}$$

3.1.2.3 η_3-cycle time simple moving average—finding the number of cycle times of MV This paper introduces the input constructs of the ANFIS prediction model using two-cycle time and three-cycle time simple moving average methods. In support of the present cycle time τ, Eqs. (2) and (3) are used to calculate the two-cycle time $MV_2(\tau)$ and three-cycle time $MV_3(\tau)$ of e-order arrivals, correspondingly, as follows:

$$MV_2(\tau) = \frac{Q_d(\tau) + Q_d(\tau - 1)}{2} \tag{2}$$

$$MV_3(\tau) = \frac{Q_d(\tau) + Q_d(\tau - 1) + Q_d(\tau - 2)}{3} \tag{3}$$

To summarise, by presenting the one-order momentum framework (MM(1)), in concert with three-time (MV(3)) and two-time (MV(2) simple moving average and one-order autoregressive interval construct (RG(1)) simultaneously, two separate groups of input constructs are found for both concepts, as displayed in Fig. 3:

- Framework I: RG(1)MM(1)MV(2) framework, i.e., a framework with one-order RG, one-order MM and two-cycle-time MV. This framework subsequently predicts ʃ(μ), i.e., e-order arrival at time $\tau+1$.
- Framework II: RG(1)MM(1)MV(3) framework, i.e., a framework with one-order RG, one-order MM and three-cycle-time MV. This framework subsequently predicts ʃ(μ), i.e., e-order arrival at time $\tau+1$.

Computing the values of RG, MM and MV for the entire data inspection of every dataset. Figure 4 exhibits the case illustration of how input values are calculated to predict the subsequent time's e-order arrival employing frameworks I and II. When ŋ×ɱ ANFIS-empowered forecasting frameworks are produced, ŋ framework structure variations and ɱ e-retailers exist. Thus, the case illustration using two framework structure variations and three e-retailers generates six ANFIS frameworks developed in concept A. For example, Fig. 4 shows that in Framework I, e-order arrival rate is calculated in two cycle times (i.e. 12 and 17), RG(1) signifies the second rate (i.e.,17), MM(1) is the difference of the two rates (17–12 = 5), and MV(2) is the sum of the two rates (12 + 17) divided by 2. While in Framework II which uses three cycle times, the MV(3) is the sum of the two rates divided by 3. In concert with an extra two ANFIS frameworks developed in concept B, eight ANFIS frameworks are proposed and developed in sum. Table 3 summarises the ANFIS frameworks proposed for concept A and B. Table 3

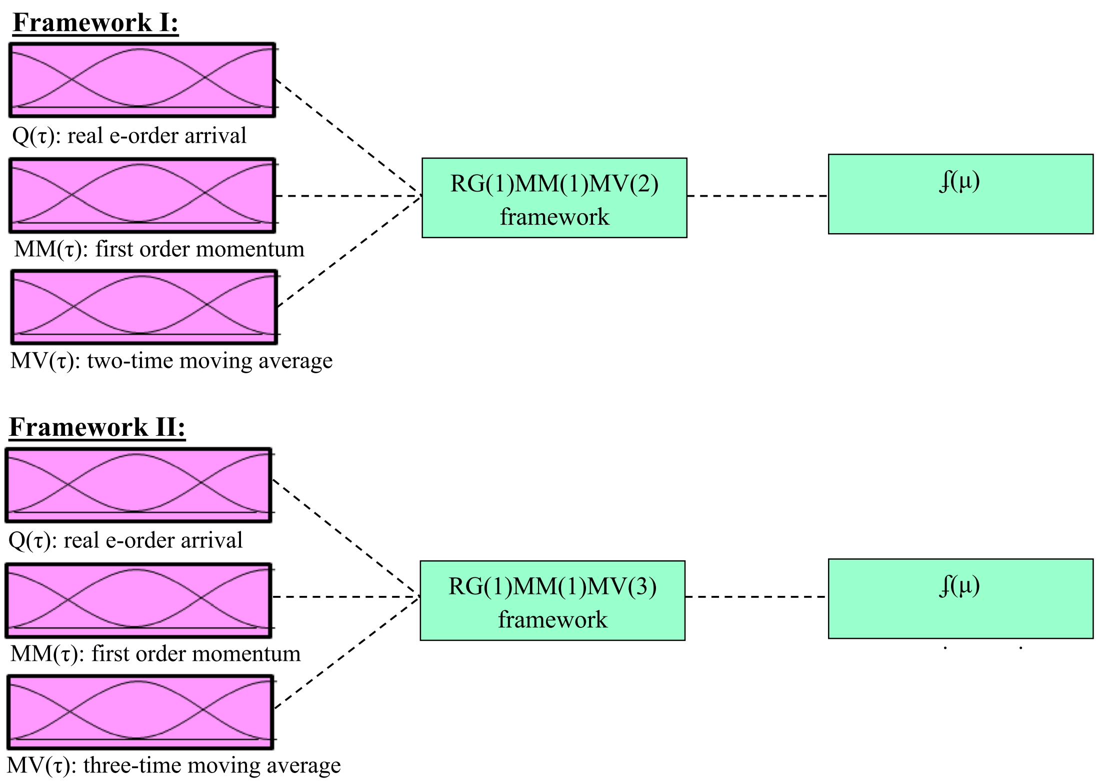

Fig. 3 Framework structure variations for frameworks I and II

	Framework I: RE(1)MM(1)MV(2)					**Framework II:** RE(1)MM(1)MV(3)				
Week	Hour	E-order arrival rate	RG(1)	MM(1)	MV(2)	Hour	E-order arrival rate	RG(1)	MM(1)	MV(3)
τ-1	15:00-18:00	15	-	-	-	15:00-18:00	**15**	-	-	-
	18:00-21:00	**12**	-	-	-	18:00-21:00	**12**	-	-	-
	21:00-24:00	**17**	-	-	-	21:00-24:00	**17**	-	-	-
τ	12:01-03:00	17	**17**	**5**	**14,5**	12:01-03:00	17	**17**	**5**	**14,7**
				[=17-12]	[=(17+12)/2]			17	[=17-12]	[=(15+12+17/3)
	03:00-06:00	15	17	0	17,0	03:00-06:00	15		0	15,3
	06:00-09:00	13	15	-2	16,0	06:00-09:00	13	15	-2	16,3
	09:00-12:00	13	13	-2	14,0	09:00-12:00	13	13	-2	15,0
	12:00-15:00	27	13	0	13,0	12:00-15:00	27	13	0	13,7
	15:00-18:00	42	27	14	20,0	15:00-18:00	42	27	14	17,7
	18:00-21:00	65	42	15	34,5	18:00-21:00	65	42	15	27,3
	21:00-24:00	80	65	23	53,5	21:00-24:00	80	65	23	44,7

Fig. 4 An illustration of the input values for frameworks I and II

Table 3 A brief of ANFIS frameworks proposed for concept A and B

Concept	Dataset	Framework I: RG(1)MM(1) MV(2)	Framework II: RG(1)MM(1) MV(3)
A	E-retailer 1	Framework 1-I	Framework 1-II
	E-retailer 2	Framework 2-I	Framework 2-II
	E-retailer 3	Framework 3-I	Framework 3-II
B	Combines all data of e-retailers	Framework 4-I	Framework 4-II

shows that while concept A assesses the dataset of individual e-retailer for each framework I and II, concept B assesses the combined dataset of the three e-retailers and the aggregated framework I and II.

3.1.3 Methodological aspects of ANFIS frameworks

The construction of ANFIS involves 5-set layers. This study has one output, i.e., the upcoming time e-order arrivals, and three inputs, i.e., RG, MM and MV, to combine the ANFIS framework and the suggested input constructs. In brief, this paper introduces a basic ANFIS framework using only one output ʃ and two inputs, χ and γ. The ANFIS' system structure comprises two sections, namely assumption and effect. Based on Takagi and Sugeno (1985), when a common first-order-fuzzy inference approach, two fuzzy if–then policies is presented as:

$$Policy\ 1{:}\ if\ \chi\ is\ \acute{A}_1, and\ \gamma\ is\ \acute{B}_1, then\ \mathfrak{f}_1 = p_1\chi + q_1\gamma + r_1$$

$$Policy\ 2{:}\ if\ \chi\ is\ \acute{A}_2, and\ \gamma\ is\ \acute{B}_2, then\ \mathfrak{f}_2 = p_2\chi + q_2\gamma + r_2$$

with $\acute{A}_i$ and $\underset{i}{\overset{\prime}{B}}$ imply the fuzzy series, p, q and r signifies linear output parameters verified in the training activity, and $\mathfrak{f}_i$ denotes the output set in the fuzzy area stipulated through the fuzzy policy.

The 1st layer. When $O'_{1,i}$ symbolizes the output of the i^{th} nodule, χ signifies an input to nodule *i*, $\acute{A}_i$ implies the input's linguistic tag, e.g., high and low, and $\mu\acute{A}_i(\chi)$ represents the relationship function (RF) in a specific shape. Every nodule *i* is a square nodule with the following nodule equation:

$$O'_{1,i} = \mu\ \overset{\prime}{A}_i(\chi) = \frac{1}{1 + \left(\frac{\chi - c_i}{a_i}\right)^{2bi}} \quad for i = 1,2 \tag{4}$$

with the RF owns a parameter group of $\{a_i, b_i, c_i\}$. Moreover, Jang (1993) states that any constant differentiable functions, e.g., frequently employed triangular-or trapezoidal-shaped RF, are similarly fit nominees for nodule functions. Various shapes are examined to produce the most acceptable framework structure for the case illustration.

The 2nd layer. Each nodule in the 2nd layer is a circular nodule symbolised by Π, which increases the entering motions and transmits the products out. Equation (5) calculated this layer's output, $\underset{i}{\overset{\prime}{\omega}}$, which signifies the triggering power of every policy, as follows:

$$O'_{2,i} = \overset{\prime}{\omega}_i = \mu\ \overset{\prime}{A}_i(\chi)\mu\ \overset{\prime}{B}_i(\gamma) \quad for i = 1,2 \tag{5}$$

The 3rd layer. Every set nodule in the 3rd layer is a circular nodule labelled by an Ń code. This layer's output, ω_i, signifies the relation of the i^{th} nodule triggering power with the total of the triggering power of the entire policies. Thus, this output is frequently considered as a standardised triggering force and presented by Eq. (6):

$$O'_{1,i} = \overline{\overset{\prime}{\omega}_1} = \frac{\overset{\prime}{\omega}_i}{\sum \overset{\prime}{\omega}_i} = \frac{\overset{\prime}{\omega}_i}{\overset{\prime}{\omega}_1 + \overset{\prime}{\omega}_2} \quad for\ i = 1,2 \tag{6}$$

The 4th layer. Every adaptive nodule in the 4th tier is a square nodule computing the role of the i^{th} nodule on the total output. This layer's factors implies effect parameters, $\mathfrak{f}_i$ denotes the fuzzy if–then policies where $\{p_i, q_i, r_i\}$ act as the parameter set, as signified by the following equation:

$$O'_{4,i} = \overline{\omega}_i\mathfrak{f}_i = \overline{\omega}_i(p_i\chi + q_i\gamma + r_i) \quad for\ i = 1,2 \tag{7}$$

The 5th layer. The separate set nodule here is a circular nodule indicated by a Σ code, which calculates the total output of the system by computing the aggregate contributions of the entire policies:

$$O'_{5,i} = \sum \overline{\omega}_i\mathfrak{f}_i = \frac{\sum \acute{\omega}_i\mathfrak{f}_i}{\sum \acute{\omega}_i} = \mathfrak{f} = total\ output \quad for\ i = 1,2 \tag{8}$$

More methodological mechanisms and features empowered by the standard ANFIS design, such as learning and training algorithms, can be found in the studies conducted by Karaboga and Kaya (2019) and Jang (1993).

3.2 Using prediction method with case illustration

This part systematically presents the subsequent processes of the construction of the prediction method. According to their actual operative data, these processes are vital to delivering comprehensive and practical implementation instruction

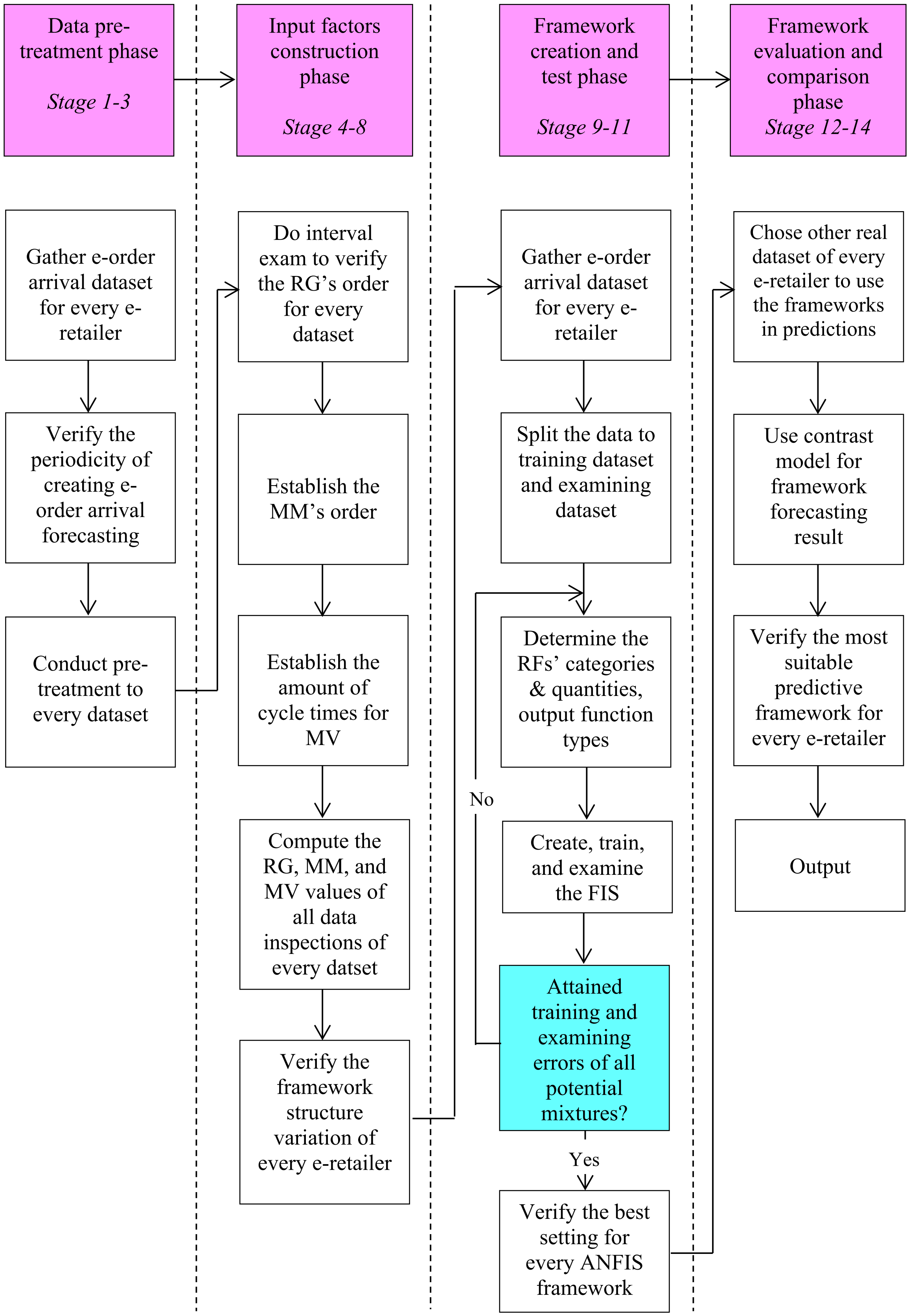

Fig. 5 Flowchart of the work: a four-phase deployment model for e-order arrival forecasting in actual operation

for business leaders through suitable prediction frameworks. A four-phase deployment model is created, as presented in Fig. 5, which also illustrates the flow chart of the work, comprising Phase I—data pre-treatment phase, Phase II—input parameters arrangement phase, Phase III—framework creation and examination Phase and Phase IV—framework evaluation and comparison phase.

3.2.1 Data pre-treatment phase

In this Phase, actual datasets from logistics business leaders are gathered and pre-treatment for the subsequent framework development. There are three stages in this Phase.

Stage 1–Gather e-order arrival dataset of every e-retailer. The testing and training activities are a robust framework for developing an ANFIS framework with good forecasting ability. For practical training and then testing the frameworks, the authors survey the e-order fulfilment practices in the distribution hub to collect and obtain actual production dataset(s). In the case illustration, as presented in the earlier part of this paper, three individual datasets are obtained from three e-retailers. Business leaders, especially 3PLPs, can obtain the data of e-order arrivals from their retail associates to construct their prediction method.

Stage 2–Verify the periodicity of e-order entry forecasting. This study employs the ANFIS-empowered framework to make the predictions of nearly-real-time e-order arrivals for every e-retailer. The framework is applied at the finale of the present period to predict the subsequent-period e-order arrivals. As an illustration, when the "period" is pre-specified as two hours, the managers obtain the anticipated e-order amount from a particular e-retailer in the next two hours employing the framework, reinforcing the 3PLP verify the volume of supplies distributed in every area in the coming period. Two elements used to determine the length of a "period" is summarised as follows:

- The existing highest order managing capability, i.e., an approximation of the most significant volume of orders (in kilograms) that accessible resources can tackle. Under the assumption, all resources, e.g., order pickers and order picking utensils, are entirely useless and can be distributed entirely for order management when being published in consignment for wholesale operation in the distribution hubs.
- The mean quantity of e-orders arrived hourly are gathered using past order-arriving performances. Usually, verifying an order clustering rotation period that will not surpass the existing highest order managing capability to evade possible overcapacity of resources, mainly the order picking workers, is a rule of thumb in an actual operative setting.

Stage 3–Pre-treatment the data for every dataset. With the time limit evaluation cycle found, the gathered datasets enter the pre-treatment stage and are used for the suggested ANFIS frameworks after being transformed to valuable input values. An eight-week actual production dataset, comprising 448 datasets in sum, is collected from the case firm's distribution hub in which the e-order fulfilment processes occur (see the case illustration in Part 3). With a time limit evaluation series verified via Stage 2, the dataset experiences pre-treatment to show the order arrival performance on a three-hour basis (see Fig. 5).

3.2.2 Input parameters arrangement phase

The input parameters proposed in the research for predicting e-order arrivals are arranged for the chosen datasets of every e-retailer. Five stages are included in this Phase, which is systematically presented in Part 3.

Stage 4–Execute interval examination to find the order of RG for every dataset.

Stage 5–Establish the MM.

Stage 6–Establish the number of cycle times for MV.

Stage 7–Compute the RG, MM and MV values of the entire data inspections in every dataset.

Stage 8–Find the framework structure variation of every e-retailer.

3.2.3 Framework creation and examination phase

Prediction frameworks are developed for the dataset of every e-retailer in this Phase. The calculation attempt in the framework construction activity relies on the framework structure variations verified in the earlier Phase. For generating and obtaining the most suitable framework setting of every built predictive framework for every dataset, five consecutive stages are generalised:

Stage 9–Split the data into a training dataset and examining the dataset. The dataset in Phase I must be divided into two datasets: training dataset and examining dataset. Typically, the training dataset consists of 70 per cent or 90 per cent of the total data. On the other hand, the residual data act as the examining dataset that can be employed to train and develop the adaptive system. In contrast, the examining dataset is applied to verify whether the framework's modelling error happens in training. Besides, cross-confirmation must be executed for data simplification scrutiny if only one dataset is existing. Thus, the trained framework in various mixtures of settings is employed with the examining dataset for avoiding the framework from overfitting the training dataset and checking the built neural system's simplification capacity. The ANFIS' best framework setting will further be verified. Using the case firm as an illustration, from the

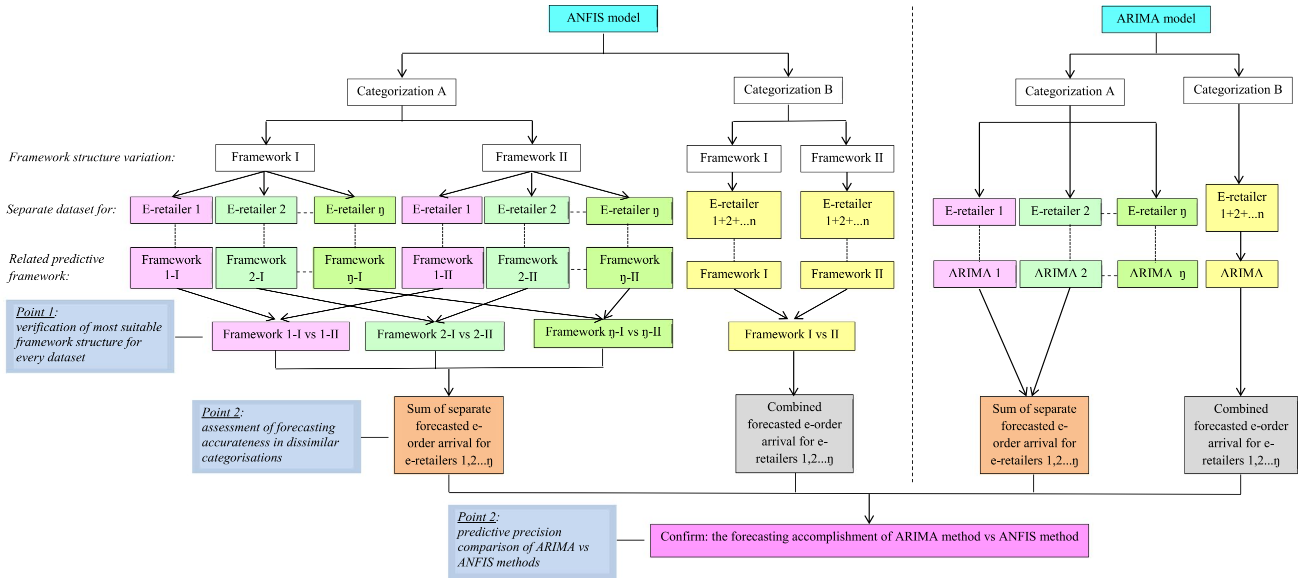

Fig. 6 A systematised contrast for cross-confirmation of framework accomplishment

eight-week actual datasets, which consist of 448 inspections in sum, 56 inspections are employed as the examining dataset to determine if any overfitting of the framework happens throughout the training. Simultaneously, the initial seven-week, i.e., 392 inspections, are employed to train and develop the adaptive system. Also, other datasets from every e-retailer are obtained to ensure the presence of data simplification stuff.

Stage 10–Determine the categories of relationship functions (RFs), quantities of RFs, output function types. System factor adjustments are vital to get the best outcome produced from the ANFIS framework. Employing the MATLAB's ANFIS editor, various categories of RFs, e.g., Gaussian curve (Gaus), generalised bell (Gbel), trapezoidal (Trap), and triangular (Tria), are accessible for choice. Besides, the categories of output RFs (either linear or constant) and the quantity of RFs for every input can similarly be adjusted. The most acceptable mixture of an ANFIS-empowered predictive framework should be verified because of the abundance of potential mixtures of the factor settings.

Stages 11–Create, train, and examine the FIS to verify the most suitable setting for every framework. Due to an abundance of variants of framework settings which should be assessed to identify the most acceptable mixture of setting, the testing error and training error in every mixture of framework settings are extracted for further comparative tests in the later phase.

4 Framework evaluation and comparison phase

Here the chosen predictive frameworks for the dataset of every e-retailer are weighed against the ARIMA framework for the subsequent performance confirmation. Three stages of confirming the viability of the built frameworks of e-order arrival forecasting in the actual logistics operational setting include:

Stage 12–Chose other actual datasets of every e-retailer for adopting the frameworks to make predictions. Other actual datasets are collected from the relating e-retailers to examine and confirm the predictive performance of every framework. Next, these datasets enter the pre-treatment stage to be transformed to the input values for every predictive framework, like the processes described in Stage 3—pre-treatment the data for every dataset—for later assessing the relevant framework's forecasting precision.

Stage 13–Use the framework contrast model for framework forecasting accomplishment. As displayed in Fig. 6, a structured comparison model is built as an arrangement for business leaders to execute cross-confirmation of the prediction frameworks' accomplishment gradually. There is a sum of ŋ x ɱ ANFIS-empowered predictive frameworks that need efficient performance assessments for ŋ framework structure variants and ɱ e-retailers.

Stage 14–Verify the most suitable predictive framework for every e-retailer. Successful comparison of the built ANFIS frameworks with the ARIMA frameworks can be achieved by measuring the forecast accurateness of these methods employing mean absolute percentage error (MAPE), mean absolute deviation (MAD), and root-mean-square error (RMSE).

5 Results

As displayed in Fig. 6, the structured assessment model involves three points for methodically assessing the predictive capability of every model and concept, which facilitate business leaders to assess the effectiveness of their prediction frameworks. Figure 6 illustrates clearly that ANFIS model is compared to ARIMA model in data prediction. First, each model assesses: (1) separate dataset for three e-retailers, (2) related predictive model, (3) assessment of forecasting acurateness in dissimilar concept/categorisation. Then, this study compares the prediction precision of ANFIS versus ARIMA model, and confirms the forecasting performance of the two models. The authors implement this assessment construction to evaluate the predictive performance of the eight ANFIS-empowered frameworks built in two concepts in the case illustration.

5.1 Verification of most suitable framework structure for every dataset

Via the framework training and examining activities for the ANFIS predictive frameworks built-in support of the case firm, the training and examining errors of every framework in various framework settings are verified. The lowest examining deviation indicates the most suitable framework setting. A brief of the most suitable setting for every framework, i.e., frameworks 1-I, 1-II, 2-I, 2-II, 3-I, 3-II, 4-I and 4-II, is presented in Table 4. Every framework is later examined with the examining dataset employing the consistent training dataset for every e-retailer. Some main results are attained:

Result 1. Categories and quantity of RFs—Gaus, Gbel, Trap, and Tria relationship functions are employed for framework training and examining. Findings displayed in Table 4 show that no particular category of RFs surpasses the others. It proposes that other categories of RFs must be examined throughout the framework training and examining activities for further employment. Regarding the quantity of RFs, inputs with two RFs primarily provide superior predictive accomplishment. RFs above four will significantly enhance the calculation time and need more extensive training dataset. Findings show that the most suitable framework can be attained for several input constructs with 2 RFs. Thus, in employing the predictive framework, constructing the inputs with two RFs is satisfactory to lessen the time spent and effort in the model in the training activity.

Result 2. The framework I vs II—A contrast between framework I (RG(1)MM(1)MV(2)) and framework II (RG(1)MM(1)MV(3)) according to examining signifies that framework II surpasses framework I in the entire E-retailers dataset, and in the combined E-retailers e-order arrival dataset. It proposes that constructing a three-cycle time moving average input construct provides an improved predictive accomplishment than a two-cycle time moving average. Frameworks 1-II, 2-II, 3-II and 4-II are proved to be the most suitable frameworks for predicting the e-order arrival of every e-retailer and the combined dataset, correspondingly. Table 4 displays that the most suitable framework for every retailers' dataset is determined by the examining error of each framework; thus, the best framework for concept A are framework 1-II with error of 9.4112 (less than the error of 1-I), 2-II with error of 11.3307 (less than 2-I), and 3-II with error of 10.4674 (less than 3-I); while the best for concept B is framework 4-II with error of 27.8764 (less than the error of 4-I).

5.2 Assessment of forecasting accurateness in distinct concepts

Employing the one-week dataset, the predictive accomplishment of frameworks 1-II, 2-II, 3-II and 4-II, regarding MAPE, MAD, and RMSE error amounts, is outlined in Table 5. Besides, every framework's item accuracy is similarly computed to verify the ratio of inspections inside the acceptable limit of error. Based on the case firm's business specialists, a forecasting error of $\pm$ 10 kg is a tolerable limit. Thus, for the single datasets of the three e-retailers, the prediction is reckoned to be accurate when an inspection using MAD is below ten. Regarding the dataset that combines order arrivals of e-retailers 1,2, and 3, an inspection is reckoned to be accurate when MAD is below 30 kg.

Result 3. Framework accomplishment in forecasting the e-order arrivals of single e-retailers –Table 5 shows that framework 1-II, 2-II and 3-III has excellent performances in estimating the e-order arrivals of e-retailers 1, 2 and 3 correspondingly. Such as, when the MAD value signifies the average absolute error among the actual and predicted e-order arrival performance (in kilograms), the MAD values of 4.743, 6.205, and 4.326, correspondingly, for frameworks 1-II, 2-II and 3-II signify that only four to six kilograms of prediction error do exist in forecasting the imminent three-hour e-order arrival. Moreover, the total item precision is proved to be more than 85 per cent. Frameworks 1-II and 3-II even outperform 90 per cent item accurateness, as only 2 and 3 of 56 items in sum are not accurate. This forecasting accomplishment of separate retailers e-order arrival demand shows high potential.

Result 4. Concept A vs B—Remember that in concept A, the e-order arrival performances for e-retailers 1, 2 and 3 are individually estimated by frameworks 1-II, 2-II and 3-II. In concept B, framework 4-II estimates the overall e-order arrival performances in the next cycle time, irrespective

Table 4 The most suitable framework structure for every prediction framework

Concept	E-retailer	Framework	Error	No. of RFs correspondingly for RG, MM, MV	Categories of RFs	Output function
A	1	1-I	10.9441	2,2,3	Gbel	Constant
		1-II*	9.4112	2,4,2	Tria	Constant
	2	2-I	11.7183	2,2,2	Tria	Constant
		2-II*	11.3307	2,2,2	Tria	Constant
	3	3-I	11.0444	3,2,2	Gaus	Constant
		3-II*	10.4674	4,2,2	Gbel	Constant
B	Combined e-order arrival of all e-retailers	4-I	28.6649	2,2,4	Gbel	Constant
		4-II*	27.8764	4,2,2	Gbel	Constant

*Signifies the most suitable framework for every retailers' dataset (concerning examining error)

of the volume of e-orders owned by a particular e-retailer. Hence, to contrast the forecasting result of concepts A and B, the overall e-order arrival performances must be calculated by adding up the separate e-order arrival performances estimated for e-retailers 1, 2 and 3, and individually estimated by frameworks 1-II, 2-II and 3-II in concept A as displayed in Fig. 2. Next, the predictive accuracy of concepts A and B can be contrasted with the one-week accurate e-order arrival data that combine the e-order arrivals for the three e-retailers.

Table 5 presents the error examination findings implying that concept B (employing one combined dataset) has fewer errors regarding MAPE, MAD, and RMSE than concept A (employing three individual datasets and then summing up every estimated value). However, the errors generated by concepts A and B are very near. Both concepts produce an insignificant error, showing predominantly high accuracy in predicting the coming period's e-order arrival employing the two concepts. Besides, item precision comparison signifies that no inspections have an error of above 30 kg. Hence, both concepts perform 100 per cent item precision. Error examination gives robust proof that the two concepts framework nearly-real-time e-order arrival is excellent.

5.3 Forecasting accurateness' contrast between ARIMA and ANFIS method

For meaningful forecasting accomplishment contrast among the ARIMA and ANFIS methods, the eight-week dataset is employed to develop the ARIMA(p,q)(r,s) framework; it is the same dataset applied for training examining the ANFIS frameworks. Initially, the most significant number of the RG, MV, seasonal moving average (SMV), and seasonal autoregressive (SRG) terms, for instance, the frequency of cyclical terms employing the EViews software and the ARIMA framework's p, q, r, s, are chosen. After that, three ARIMA frameworks are developed in concept A for forecasting the e-order arrivals of the three e-retailers individually, and an ARIMA framework is developed in concept B for forecasting the overall e-order arrivals. Error examination is later conducted by contrasting the estimated e-order arrival results regarding the one-week real dataset. The results are presented as follows:

Result 5. ARIMA vs ANFIS frameworks—In concept A, as the e-order arrival accomplishments of e-retailers are individually predicted by their relevant ARIMA and ANFIS frameworks, the error examination presented by Table 5 signifies that the ARIMA-empowered method underperforms the ANFIS-empowered method. Table 5 shows that ARIMA(4,1)(1,1) performs much more errors than framework 4-II (i.e., RMSE = 24.649 > 12.929; MAD = 20.546 > 10.075; MAPE = 14.0% > 6.1%). Thus, the suggested ANFIS-empowered forecasting method in the paper that uses the incorporation of time sequence data features as the input constructs is empirically confirmed to be better than the ARIMA method in estimating e-order arrivals.

6 Discussion

The empirical findings of this study reveal that concept B has a superior predictive outcome than concept A in both the ARIMA-empowered and ANFIS-empowered methods. Thus, the final contrast between ARIMA and ANFIS is by contrasting the predictive outcome of ARIMA framework in concept B with that of ANFIS framework in concept A, i.e., ARIMA(4,4)(1,1) vs framework 4-II. Table 5 shows that ARIMA(4,1)(1,1) performs much more errors than framework 4-II. Intriguingly, the MAPE, MAD, and RMSE employing the ANFIS-empowered method are half those employing ARIMA(4,1)(1,1). It means that the suggested ANFIS-empowered method performs a statistically 200% superior predictive accomplishment than the traditional

Table 5 Error examination for ARIMA and ANFIS framework contrast

	Concept	A		A		A		A	B	
		E-retailer 1		E-retailer 2		E-retailer 3		Total forecasted e-order arrival of every e-retailer by Framework 1-II. 2-II. 3-II	Combined dataset	
	Framework	1-II	ARIMA (4.1)(1.1)	2-II	ARIMA (3.4)(1.1)	3-III	ARIMA (3.4)(1.1)		4-II	ARIMA (4.1)(1.1)
1	RMSE	5.505	8.856	7.536	11.507	5.220	9.699	13.680	12.929	24.649
2	MAD	4.743	7.343	6.205	9.506	4.326	7.861	12.096	10.075	20.546
3	MAPE	11.1%	18.7%	11.3%	17.7%	7.4%	17.1%	7.9%	6.1%	14.0%
4	Item precision	96.1%	81.7%	88.9%	63.5%	94.4%	72.5%	100.0%	100.0%	79.8%
5	Total items	56	56	56	56	56	56	56	56	56
6	No. of accurate items	54	46	50	36	53	41	56	56	45
7	No.of inaccurate items	2	10	6	20	3	15	0	0	11

ARIMA framework in predicting e-order arrival. Concerning item accurateness comparison, the suggested ANFIS framework also shows no contrast with the ARIMA model, with 100 per cent item precision for ANFIS and only 79.8 per cent item accurateness for ARIMA.

Overall, the suggested ANFIS method that incorporates the components of RG, MM, and MV for framework construction is proven to outperform the ARIMA method and more significant in predicting both separate and combined e-order arrivals in distribution hubs. The mining of separate actual datasets of the three e-retailers for constructing both ARIMA and ANFIS frameworks confirms the suggested input settings' predictableness incorporated with the ANFIS method to predict e-order arrivals.

This paper provides several practical implications. First, nearly-real-time order demand forecasting's practicality empowers operational, tactical, and strategic management for logistics business leaders and other practitioners in the SC. In the operational context, managers who conduct the fulfilment activity of the e-orders subcontracted from many e-retailers must use their accessible past data to predict the nearly-real-time order arrivals to be proactively aware of the following order arrival quantity in the upcoming several hours. It will give them enough time to distribute the optimal quantity of supplies in distribution hubs for tackling the coming e-orders when they appear. This proactive method in managing appropriate resource distribution according to real-time order forecasting is hardly discovered because the present warehouse managing activity is slightly reactive in the lack of forecasting. Thus, managers are inclined to be reactive, e.g., redistribute resources according to the actual order arrivals.

Tactically, in today's multi-channel age, every product label is marketed over various marketing channels, offline and online. Prediction can similarly be conducted regarding the e-order demand from every marketing channel or every geographic area. It enables managers to tactically reckon the distribution and shipping of an appropriate volume of final products to chosen distribution centres to fulfil the order from the channels and the geographic locations. Strategically, e-retailers and producers can utilise the method to predict the selling performance of every product type across a time limit, facilitating them to make particular strategic objectives for every product label or modify production volumes correspondingly.

Thus, the suggested method inspires managers to transform the reactive into proactive management of warehouses. The suggested data-empowered method incorporating time sequence data features can cover broader implementations in many vertical businesses for improved decision-making with a highly accurate prediction.

7 Conclusion and implications

The paper is a novel study that presents an ML forecasting method for predicting nearly-real-time e-order arrivals in distribution hubs using ANFIS compared to ARIMA model. As contrasted to earlier publications in the SC, this suggested methodology overpowers the shortcoming of broader time lags, e.g., monthly and weekly for operation management. In the e-commerce age, e-order arrival characteristics have increased the necessity to conduct demand forecast in a much nearer lag for creating more effective decision support. Inspired by those matters, the paper tries to fill the literature gap by developing nearly-real-time e-order arrivals via the adoption and use of accessible data from downline e-retailers, i.e., historical order arrival date. The features of time sequence data, such as moving average, volatility, and autoregressive components, are incorporated into the suggested data-empowered method as the input constructs for framework establishment.

This study's findings have several theoretical and practical implications. Theoretically, this study develops a new machine learning forecasting method by integrating an ANFIS and time-series data features, and finds that the model is successful in predicting e-order arrivals accurately. This finding reinforces the previous literature which reveals that the ML forecasting model which integrates ANFIS and time-series data is effective in predicting various sectors, such as food production (Nosratabadi et al. 2021), oil production (AlRassas et al. 2021), complex stock market (Alenezy et al. 2021; Hussain et al. 2022), river flows (Riahi-Madvar et al. 2021), and blood pressure (Zardkoohi and Molaeezadeh 2022). This paper also supports earlier findings that ANFIS significantly reduce the issues' computational complexity (Asghar and Liu 2018). This study broadens the existing literature by focusing the use of new ML-ANFIS-time-series data prediction model on e-logistics sector which has been neglected by other scholars. This study' methodology uses hourly basis prediction, which overpowers the limitations of broader time lags, e.g., monthly or weekly, for managing daily operations.

Next, this study employs a descriptive case study and shows a satisfactory degree of precision of the suggested ML method in predicting the actual e-order arrivals in three e-retailers at three-hour cycle times. The findings reveal that the real-time forecasting is significant to boost the values of e-order arrivals in every day business operations; which supports the outcomes of existing literature (D'Haen et al 2022; Ho et al. 2022). This study's findings extend the literature by predicting hour-to-hour, actual-time order arrivals, which has been ignored by previous scholars as they investigate SC orders and prediction issues in a broader space.

Regarding practical implications, this study's findings provide a method for predicting real-time e-orders arrivals in distribution hubs, enabling third-party logistics providers to handle the hourly-based e-order arrival rates more efficiently. These findings fill the space of knowledge as an earlier publication suggests that the flourishing of e-retail performances in SC management has dramatically affected the latest e-logistics operative flow (Zhu and Liu 2021). This paper contributes to logistics and SC management literature by delivering an effective tool to predict the prospect of real-time e-order arrivals in e-retailers, thereby helps to improve e-retailer performances. Academicians, managers, and decision-makers can adopt this framework to forecast an hour-to-hour order arrivals in their fields or businesses.

8 Future works

This paper provides the prediction of e-order arrivals which is merely based on time-series data, considering other aspects like service degree, number of transport devices, delivery costs, and technological innovations as constant. Thus, scholars can fill this space by examining the abovementioned aspects in their future works. This paper also generalizes the findings that the ANFIS framework surpasses the ARIMA framework as time-series data restricts the result and the outcomes can vary in data associated with other company/business. Hence, upcoming works can be conducted to employ available data the SCs through the combination of prediction methods and heuristics or optimisation techniques for improved decision-making in SC management. Future works ara also advised to use this research framework to predict e-order arrivals in various firms and industries and deliver proper resolutions to fight innefective SC management. Besides, related research in other SC perspectives is important to be done before oversimplifying the study's results. Different ML methods like Support Vector Machine (SVM) and its extended versions can be used in related situations, which can minimalize the data noise because of outliers in training series enhancing the organizer accomplishment (Kamble et al. 2021). The results of such works can be interesting and and very useful for managers and decision-makers.

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Declarations

Conflict of interest All authors proclaim that they have no competing interest.

Ethical approval All processes accomplished in research containing human contributors were compliant with the ethical standards of the institutional.

Informed consent Informed consent was gotten from all individual contributors involved in this research.

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