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Hybrid structures in time series modeling and forecasting: A review ☆

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ABSTRACT

The key factor in selecting appropriate forecasting model is accuracy. Given the deficiencies of single models in processing various patterns and relationships latent in data, hybrid approaches have been known as promising techniques to achieve more accurate results for time series modeling and forecasting. Therefore, a rapid development has been evolved in time series forecasting fields in order to access accurate results. While, numerous review papers have been concentrated on the use of hybrid models and their advantages in improving forecasting accuracy versus individual models in wide variety of areas, no study is concerned to categorize and review papers from the structural point of view in numerous developed studies. The main goal of this paper is to analyze hybrid structures by surveying more than 150 papers employed various hybrid models in time series modeling and forecasting domains. In this paper, the classification of hybrid models is made based on three main combination structures: parallel, series, and parallel–series. Then, reviewed papers are analyzed comprehensively with respect to their specific features of employed hybrid structure. Through reviewed articles, it can be observed that combined methods are viable and accurate approaches for time series forecasting and also the parallel–series hybrid structure can obtain more accurate and promising results than other those hybrid structures. Besides this paper provides the viable research directions for each hybrid structure to help the researchers in time series forecasting area.

1. Introduction

Time series forecasting is a broad and active research area which is drawn considerable attention from wide variety of fields such as finance, engineering, statistics and etc. Therefore, a large amount of literature has focused on approaches that can get accurate forecasts in numerous practical applications. In general, two main ways can be traced in the literature in order to achieve desired and accurate results and/or improve the accuracy of obtained results: (1) developing and proposing new forecasting models and (2) hybridization of existing forecasting models. Hybridization is generally performed due to the lacking of the comprehensive individual model in capturing various patterns in the data, concurrently. Undoubtedly, one model is not sufficient to deal with complex real world systems with unknown mixed patterns. Combining different models is one of the most common remedy introduced in the literature aiming to take the strength of individual models in patterns modeling and recognition applied in large amount of time series forecasting articles. Pioneer researchers such as Bates and Granger (1969), Clemen (1989); Granger and Ramanathan (1984), Hibon and Evgeniou (2005), Timmermann (2006), Winkler and Markakis (1983), Bunn (1989) and Armstrong (2001) claimed that combining different models can enhance forecasting accuracy compared with individual models used separately.

Main advantages of hybrid models enumerated in related articles can be summarized in three substantial points:

(1) Improving forecasting accuracy due to comprehensive pattern detection and modeling.
(2) Reducing the risk of using inappropriate model due to the combination of forecasts.
(3) Simplifying the procedure of model selection due to the use of different components.

According to the importance of the forecasting with high degree of accuracy, applying hybrid models for time series modeling and forecasting continues to grow in recent studies. Several review articles overviewed the hybrid forecasting models and their applications. These review papers provided different classifications of the hybrid models in specific field of time series forecasting. Tascikaraoglu and Uzunoglu (2014) generally reviewed the most widely-used hybrid models and developments in the short term wind power and speed forecasting field namely weighted based hybrid model, data preprocessing, parameter

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selection and optimization and error processing techniques. Deb et al. (2017) presented the comprehensive overview on the machine learning approaches and their hybrid models which are constructed from two or more machine learning techniques for energy consumption forecasting. Pradeepkumar and Ravi presented (Pradeepkumar and Ravi, 2018) the review on soft computing hybrid models for FOREX rate prediction. They categorized the soft computing hybrid models in to ANN based, evolutionary computation based, fuzzy logic and SVM based hybrid models. The final conclusion of this study is that ANN-based hybrids are more pervasive and more accurate hybrid techniques in the pertinent area. Rather et al. (2017) surveyed important published papers for stock market forecasting and portfolio selection. They divided reviewed articles in to two general classes including single and hybrid models. Antonanzas et al. (2016) reviewed the different techniques to generate power forecasts for photovoltaics. The hybrid models surveyed in this study followed two hybridization approaches: combining two or more statistical models (statistical hybrid models) and combining statistical models and photovoltaic performance model (physical hybrid model).

Even though some recent review articles surveyed the specific branch of hybrid models and make classification in the particular fields, none of them pay comprehensively attention to all combining structures in various hybrid time series forecasting models. Therefore, the best of our knowledge is to fill the gap in the literature by reviewing various hybrid models based on the three main structures proposed in the literature: parallel, series and parallel–series regardless of the field of study. In the next phase, each research study is analyzed based on the specific features of used combination structure. Two highlighted goals followed in this review paper are:

(1) Categorizing hybrid models proposed for time series modeling and forecasting in three main classes.
(2) Systematically analyzing articles with considering its unique characteristics of hybrid structures.

The rest of the paper is organized as following sections: In Section 2, existing hybrid methods in the literature are classified and then key concepts of combination approaches are briefly described. In Section 3, articles that proposed parallel hybrid models for time series modeling and forecasting are reviewed. In Section 4, the overview of series hybrid models is presented. Section 5 contains the main conclusions attained from analyzing hybrid structures in reviewed papers. In addition, a brief summary about the most important findings achieved by reviewing the related studies is presented at the end of each section. In the last section, conclusions are discussed. The description of all acronyms and abbreviations used in this paper are alphabetically summarized in Table 1.

2. Classification of hybrid models applied for time series modeling and forecasting

The majority of hybrid models proposed for time series forecasting can be clustered in four main classes namely (1) Data preprocessing based hybrid models, (2) Parameters optimization based hybrid models, (3) Component combination based hybrid models, and (4) postprocessing based hybrid models. Data preprocessing and parameters optimization based models are the most popular and widely-used hybrid models; respectively. The postprocessing based models have the lowest usage.

Data preprocessing based hybrid models are the most well-known category in hybridization that usually has much focus on the data preprocessing techniques. In this category, the time series is transformed into a simpler data or it is divided in to several sub data sets. For instant, Nguyen and Novák (2019) have developed a preprocessing based hybrid model to forecast seasonal time series. In this study, a time series decomposed into three main parts including a trend-cycle, seasonal, and irregular fluctuation parts. Then, each of these constituents is modeled by fuzzy transform, pattern recognition, fuzzy natural logic techniques and Box–Jenkins approach. EMD and Wavelet families are the most commonly used decomposition techniques for time series forecasting. The comprehensive analyzing on preprocessing based hybrid models is provided in some recent review papers (Qian et al., 2019; Shao et al., 2017). The brief literate review of the recent developed data preprocessing based hybrid models is given in Table 2.

The second class of hybrid models in which parameters of different forecasting models are determined by optimization models and especially Meta heuristic algorithms is the parameter optimization based hybrid models. Meta heuristic algorithms are successfully adopted in this category due to its comprehensive searching advantages (Qian et al., 2019). Ojha et al. have provided a broad overview on optimization based hybrid models developed on ANN models (Ojha et al., 2017). In addition, in several researches both preprocessing techniques and optimization algorithms have been simultaneously applied in order to improve the forecasting ability of hybrid models. Some recent studies on parameters optimization based hybrid models are summarized in Table 2.

Ensemble models are the most well-known hybrid models in the component combination based models. Recently different ensemble models have been proposed and used widely in numerous practical fields (Zameer et al., 2017; Chen et al., 2018; Song and Dai, 2017). The conceptual application of ensemble models is to improve the accuracy and additionally reducing variance. As an example, Ribeiro et al. (2019) proposed an ensemble hybrid model using WNN in which wavelet functions are utilized in a hidden layer as an activity function in neural network for short term load forecasting. Galicia et al. (2019) presented an ensemble framework composed of three models including decision tree, gradient boosted trees and random forest for big data time series. After thorough analyzing the previous review studies on this field, it can be noticed that there is no survey study concentrated on the overviewing the component based hybrid models. Thus, the main area of interest in this study is to categorize and review the component combination based hybrid models, considering their combination structure which is not addressed in the literature of time series forecasting and discussed in detail in this paper.

2.1. Component combination based hybrid structure

By reviewing component based hybrid models presented in a large amount of papers, the combination methods that are connected and combined different types of individual models can be generally categorized based on the hybridization structure in three main categories: (1) parallel, (2) series, and (3) parallel–series, which are described in three following subsections, respectively. The framework of general classification of hybrid structures considered in this study is shown in Fig. 1.

2.2. Parallel hybrid structure

Early studies in forecasting with combined models starting with Bates and Granger (1969), Newbold and Granger (1974), and Winkler and Markakis (1983) who tried to develop parallel hybrid models. Clemen (1989) made a comprehensive review on preliminary articles that used hybrid parallel models and classified them based on their contribution in different areas. Parallel hybrid structure is the most advanced combination method introduced by Bates and Granger (1969) in the initial classic study. They constructed a parallel hybrid model by linear combination of different separate sets of forecasts. They demonstrated that their proposed parallel hybrid model can lead to achieve smaller error variance that any of based models. From conceptual perspective, the procedure of parallel hybrid structure used for combining forecasting models can be defined when raw data is given to individual models, simultaneously. In the second step, the relative effectiveness of each forecast known as a component weight is determined by choosing a specific weighting algorithm. In the last stage, the weighted forecasts

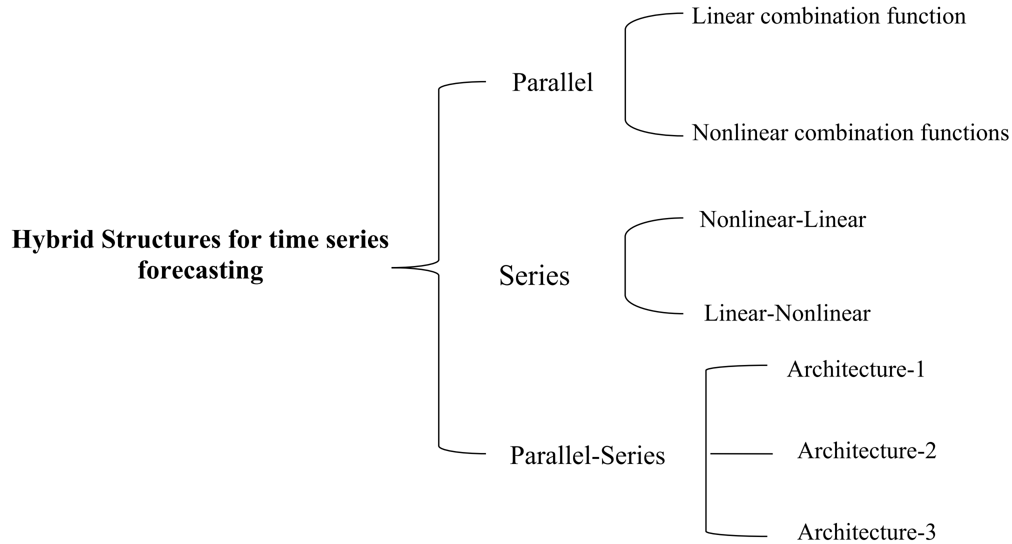

Fig. 1. The general classification of hybrid structures in this study.

are integrated by employing linear or nonlinear function as given in Eq. (1). The general framework of parallel hybrid structure is shown in Fig. 2.

$$f_{combined,t} = \varphi(w_1\hat{f}_{1,t}, w_2\hat{f}_{2,t}, \dots, w_n\hat{f}_{n,t}) \qquad t = 1, 2, \dots, T \tag{1}$$

where, φ is defined as a linear or nonlinear combination function, $w_i\hat{f}_i(i = 1, 2, \dots, n)$ is referred to weighted forecasted value of each individual model at time t, T is the number of underlying data, and n is the number of individual based models (components).

2.3. Series hybrid structure

Series combination methods were found on the concept of sequential modeling procedure. Series model was implemented for the first time by Zhang in 2003 (Zhang, 2003) for real world time series forecasting. Zhang (2003) was proven that by decomposing time series in to linear and nonlinear parts and modeling them by ARIMA and MLP models respectively, due to processing the output of ARIMA model by MLP model, the superior performance can be achieved against individual components used separately. The unique advantage of series approaches is to decompose the underlying time series in to different components and processing output of each model sequentially. In this way, the final combined forecast is achieved by summation of different forecasts, shown in Eq. (2). A general framework of series models is illustrated in Fig. 3.

$$f_{combined,t} = \hat{f}_{1,t} + \hat{f}'_{2,t} + \hat{f}'_{3,t} + \cdots + \hat{f}'_{n,t} \qquad t = 1, 2, \dots, T \tag{2}$$

where, $f_i(i = 1, 2, \dots, n)$ is the ith individual involved model, $\hat{f}_1$ is the forecasted value of the first model applied on raw data, and the $\hat{f}'_2$ is the forecasted value of the second model applied on the obtained forecasting results of previous model; and therefore, the $\hat{f}'_n$ is the forecasted value of last model applied on forecasted results of $(n-1)$th model.

2.4. Parallel–series hybrid structure

The parallel–series hybrid structure is constructed based on the combination of parallel and series hybrid concepts for extracting the advantages of both structures. This structure is generally proposed in the literature for combining two different individual models. The procedure of the parallel–series hybrid structure is initialized by parallel combination phase. In this way, the data is first given simultaneously to two components (Eq. (3)).

$$\hat{o}_1 = f_1(y_t),\ \hat{o}_2 = f_2(y_t) \tag{3}$$

where, $\hat{o}_i(i = 1, 2)$ is the output of the ith individual models. Then in the series phase, the output of first model consists of residual ($\hat{e}_t$) and forecasted value ($\hat{L}_{1,t}$), along with actual data are given to the second model in a sequential modeling form. Consequently, the final forecasting result is considered as an output of second model. Thus, based on the choosing of the output of first including: $\hat{e}_t$, $\hat{L}_{1,t}$ or both of them, as an input of second model, three possible architectures can be proposed as follows:

Architecture-1:

$$f_{combined,t} = f_2(\hat{e}_t, y_t) \qquad t = 1, 2, \dots, T \tag{4}$$

where, f_2 is a nonlinear function that are determined by an intelligent model. This architecture for the first time was proposed by Khashei and Bijari (2010) by choosing ARIMA and ANN individual models as f_1 and f_2, respectively.

Architecture-2:

$$f_{combined,t} = f_2(\hat{L}_t, y_t) \qquad t = 1, 2, \dots, T \tag{5}$$

where, $\hat{L}_t$ is the forecasted value obtained by the first model, which is selected from statistical models.

Architecture-3:

$$f_{combined,t} = f_2(\hat{e}_t, \hat{L}_t, y_t) \qquad t = 1, 2, \dots, T \tag{6}$$

This formulation of the parallel–series hybrid model is the extended work of Khashei and Bijari (2011). They verified that the proposed model can be achieved superior forecasting result compared with the constructive ARIMA and MLP models and also the ARIMA-ANN series model. The general framework of parallel–series model is shown in Fig. 4.

3. Reviewing papers

In this section, the general overview of papers that are analyzed in this review study is given. The information of articles reviewed in this study based on the number of papers in both journal and conference and the contribution of publication in each year is shown in Table 3 and Fig. 5, respectively. In Table 4 the information of reviewed papers with respect to the field of study is presented.

Table 4 represents the distribution of papers analyzed with respect to the forecasting field. As seen the most common fields used hybrid models to yield more accurate performance are the energy, financial and real data forecasting respectively. The reason is that in these

Table 1
Definitions of acronyms and abbreviations.

Acronym	Description	Acronym	Description
ABC	Artificial Bee Colony	MAE	Mean Absolute Error
ANFIS	Adaptive neuro fuzzy inference system	MAPE	Mean Absolute Percentage Error
ANN	Artificial Neural Network	MARMA	Monthly Autoregressive Moving Average
APSO	Adaptive Particle Swarm Optimization	MARS	Multivariate Adaptive Regression Splines
AR	Autoregressive	MCSO	Modified Crow Search Optimization
ARCH	Autoregressive Conditional Heteroskedasticity	MI	Mutual Information
ARFIMA	Autoregressive Fractionally Integrated Moving Average	MKRPINN	Multi-kernel regularized pseudo inverse neural network
ARIMA	Autoregressive Integrated Moving Averages	MLP	Multi-Layer Perceptron
ARIMAX	Autoregressive Integrated Moving Average with Explanatory Variable	MLR	Multiple Linear Regression
ARMA	Autoregressive Moving Average	MMAE	Minimizing the Maximum Absolute Error
ARNN	Auto-Regressive Neural Network	MOFPA	Multi Objective Flower Pollination Algorithm
BCM	Binomial Coefficient Method	MOGWO	Multi-objective grey wolf optimizer
BMA	Bayesian Model Averaging	MPLSR	Modified Partial Least Squares Regression
BPNN	Back Propagation Neural Network	MSE	Mean Squared Error
BT	Boosting Tree	MSVR	Multi-output Support Vector Regression
BSA	Backtracking Search Algorithm	NAR	Multi-output Support Vector Regression
CARDS	Coupled Autoregressive and Dynamical System	NARNN	Nonlinear Auto-Regressive Neural Network
CD	Classical Decomposition	NARX	Nonlinear Autoregressive with Exogenous inputs
CEEMDAN	Complete Ensemble Empirical Mode Decomposition Adaptive Noise	NLSVR	Nonlinear Support Vector Regression
CFBNN	Cascade Forward Back propagation Neural Network	NRLS	Non-negative Restricted Least Squares
CLS	constrained least squares	OLS	Ordinary Least Squares
CNEA	Cascaded Neuro-Evolutionary Algorithm	PANN	Periodic ANN
CPSO–CM–NNCT	Chaos Particle Swarm Optimization algorithm based on No Negative Constraint Theory	PAR	Periodic Autoregressive
CSA	Cuckoo Search Algorithm	PCA	Principal component analysis
CSO	Crisscross Optimization	PCR	Principal Component Regression
DAN2	Dynamic Architecture for ANN	PLSR	Partial Least Squares Regression
DBN	Deep Belief Net	PLS-SVM	Partial Least Square Support Vector Machine
DE	Differential Evolution	PNN	Probabilistic Neural Network
DENFIS	Dynamic Evolving Neural-Fuzzy Inference System	PSNN	Psi Sigma Neural Network
DESM	Double Exponential Smoothing Model	PSO	Partial Swarm Optimization
DMSE	Discounted mean square error	PSOGSA	Principal Component Regression
DMSNN	Direct Multi Step Neural Network	PSTM	particle Swarm Optimization and Gravitational Search Algorithms
DRESN	Double-Reservoir Echo State Network	PTTM	Predetermined Seasonal Term Method
EEMD	Extreme Learning Machine	QRM	Quadratic Regression Model
ELM	Elman Neural Network	QRNN	Quantile Regression Neural Network
ELNN	Empirical Mode Decomposition	RARIMA	Rolling Autoregressive Moving Average
EMD	Ensemble Empirical Mode Decomposition	QRM	Quadratic Regression Model
ERLS	Equality Restricted Least Squares	QRNN	Quantile Regression Neural Net-work
ERNN	Elman's Recurrent Neural Networks	RBFNN	Radial Basis Function Neural Network
ESM	Exponential Smoothing Model	RBM	Restricted Boltzmann Machines
ESN	Echo State Network	RF	Random Forest
EWT	Empirical Wavelet Transform	RMSNN	Recursive Multistep Neural Network
EX AR	Exponential Autoregressive	RNN	Recurrent Neural Network
EXP	Exponential	RW	Random Walk
FNN	Fuzzy Neural Network	SSA	Singular Spectrum Analysis
FSARIMA	Fuzzy Seasonal Autoregressive Integrated Moving Averages	SA	Simple Average
FSM	Fuzzy System Method	SAA	Simulated annealing Algorithm
FOA	Fruit Fly Optimization Algorithm	SAE	Sum of Absolute Value of Error
FFA	Firefly Algorithm	SAMCSA	Self-adaptive Modified Cuckoo Search Algorithm
GA	Genetic Algorithm	SAPSO	Self-adaptive particle swarm optimization
GSA	Gravitational Search Algorithm	SARIMA	Seasonal Autoregressive Integrated Moving Averages
GABPNN	Genetic-Algorithm-Optimized Back Propagation Neural Network	SD	Seasonal Decomposition
GA–CM–NNCT	Genetic Algorithm based on No Negative Constraint Theory	SETAR	Self-Exciting Threshold Autoregressive
GARCH	Autoregressive Conditional Heteroskedasticity	SGWO	Grey Wolf Optimization
GBRT	Gradient Boosted Regression Trees	SLM	Single Linear Model
GCPSO	Guaranteed Convergence Particle Swarm Optimization	SMA	Simple Moving Average
GEP	Gene Expression Programming	SOFNN	Self-Organizing Fuzzy Neural Network
GLAR	Generalized Linear Auto Regression	SRWNN	Stochastic Recurrent Wavelet Neural Network
GM	Gray Model	SSE	Sum of Square Error
GMDH	Group Method of Data Handling	SSVR	Single-Output Support Vector Regression
GP	Genetic Programming	STL	Seasonal and Trend
GPR	Gaussian Process Regression	SVM	Support Vector Machine
GRNN	General Regression Neural Network	SVR	Support Vector Regression
GRR	Granger–Ramanathan's Regression	SVRM	Support Vector Regression Machine
GSO	Glowworm Swarm Optimization	SWAM	Simple Weighted Average Method

(*continued on next page*)

Table 1 (*continued*).

Acronym	Description	Acronym	Description
HESM	Holt's Exponential Smoothing Method	TAR	Threshold Autoregressive
HSO	Harmony Search Optimization	TDNN	Time Delay Neural Network
HWM	Holt–Winters Method	TM	Trimmed Mean
IA-PSO	Immune Algorithm-Particle Swarm Optimization	VAR	Vector Auto Regressions
ICA	Imperialist Competitive Algorithm	Var-Cov	Variance–Covariance
ICEEMDAN	Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise	VECM	Vector Error Correction
ISCA	Improved Sine Cosine Algorithm	VMD	Variational Mode Decomposition
KELM	Kernel Extreme Learning Machine	WANFIS	Wavelet-Adaptive Neuro Fuzzy Inference System
KF	Kalman Filter	WCA	Water Cycle Algorithm
KNN	k-Nearest Neighbor	WLSP	Weighted Least Squares with Polynomial Weights
LAD	Least Absolute Deviation	WM	Winsorized Mean
LASSO	Least Absolute Shrinkage and Selection Operator	WNN	Wavelet Neural Network
LPM	Linear Perturbation Model	WOA	Whale Optimization Algorithm
LR	Linear Regression	XGBoost	eXtreme Gradient Boosting
LRNN	Layered Recurrent Neural Network		
LSSVM	Least Square Support Vector Machine		
LVGFM	Linearly Varying Gain Factor Model		
MA	Moving Average		

Table 2
Recent study on preprocessing and optimization based hybrid models.

Ref.	Year	Preprocessing Technique	Optimization Algorithm	Constructive Model
Yang et al. (2019)	2019	ICEEMDAN	MOGWO	ENN
Qu et al. (2019)	2019	CEEMDAN	Flower-Pollination	BPNN
Saâdaoui and Rabbouch (2019)	2019	Wavelet	–	ARFIMA/ANN
Wu et al. (2019)	2019	EEMD	Grasshopper	ELM
Ali and Prasad (2019)	2019	ICEEMDAN	–	ELM
Wang et al. (2019)	2019	–	BSA	ESN
Zhu et al. (2019)	2019	CEEMD	GWO, CSA	SVR
Liang et al. (2019)	2019	EMD	FOA	GRNN
Alameer et al. (2019)	2019	–	WOA	MLP
VanDeventer et al. (2019)	2019	–	GA	SVM
Chen et al. (2019)	2019	–	PSO	SVM
Jamali et al. (2019)	2019	–	PSO, GA	MLP
Jiang et al. (2019)	2019	ICEEMDAN	ICA	BPNN
Hu et al. (2019)	2019	–	GA, PSO	BPNN
Moreno and Santos Coelho (2018)	2018	SSA	–	ANFIS
Niu et al. (2018)	2018	VMD	GWO	ARIMA/SVR
Xiang et al. (2018)	2018	EEMD	–	SVR-ANN
Gholami et al. (2018)	2018	–	PSO, GA	ANFIS
Huang and Wang (2018)	2018	Discrete Wavelet	–	SRWNN
Puchalsky et al. (2018)	2018	–	ABC, GSO, GSA, ICA	WNN
Li1 et al. (2018)	2018	—	Quantum-Behaved PSO	SVR
Zhu et al. (2018)	2018	CEEMD	PSO, GSA	GRNN/SVR
Deo et al. (2018)	2018	–	FFA	MLP
Hong et al. (2018)	2018	–	HSO, PSO	GEP
Danandeh Mehr (2018)	2018	–	GA	GEP
Ch. Yu et al. (2018)	2018	Wavelet packet	–	ENN
Hu et al. (2018)	2018	–	ISCA	BPNN
Zhang and Wang (2018)	2018	SSA	CSA	ARIMA, SVR
Yang et al. (2017)	2017	Wavelet	SA, PSO	ARIMA, KELM
Xiao et al. (0000)	2017	SSA	Improved CSA	Modified WNN
Pradeepkumar and Ravi (2017)	2017	–	PSO	QRNN
Mousavi et al. (2017)	2017	–	SA	MLP
Chouikhi et al. (2017)	2017	–	PSO	ESN
Sun et al. (2017b)	2017	–	CSA	LSSVM
Yin et al. (2017)	2017	EMD, Wavelet Packet	CSO	ELM
Yaslan and Bican (2017)	2017	EMD	–	SVR
Zhang et al. (2017b)	2017	SSA	CSA	SVM
Zhong et al. (2017)	2017	–	GA	DRESN
Hussain and AlAlili (2017)	2017	Discrete Wavelet	–	MLP, ANFIS, NARX, GRNN
Jianwei et al. (2017)	2017	VMD	–	ARIMA
Zhang et al. (2017a)	2017	EEMD	–	KNN

fields data sets have the highest level of complexity and including several different structures simultaneously. So, the hybridization can be a promising strategy to process and capture different patterns in data more accurately.

3.1. Reviewing the parallel hybrid structure in time series forecasting

There are several studies in which the similar concept of parallel hybrid method proposed by Bates and Granger (1969) have been used and tried to develop this structure for time series modeling and forecasting. The key step in constructing parallel model is choosing linear or nonlinear combination function and appropriate weighting approach. Thus, the classification in this paper is constructed based on specific characteristics of this structure combination function and weighting approaches. The combination function is proposed in two linear and nonlinear forms, which related articles are reviewed in following subsections.

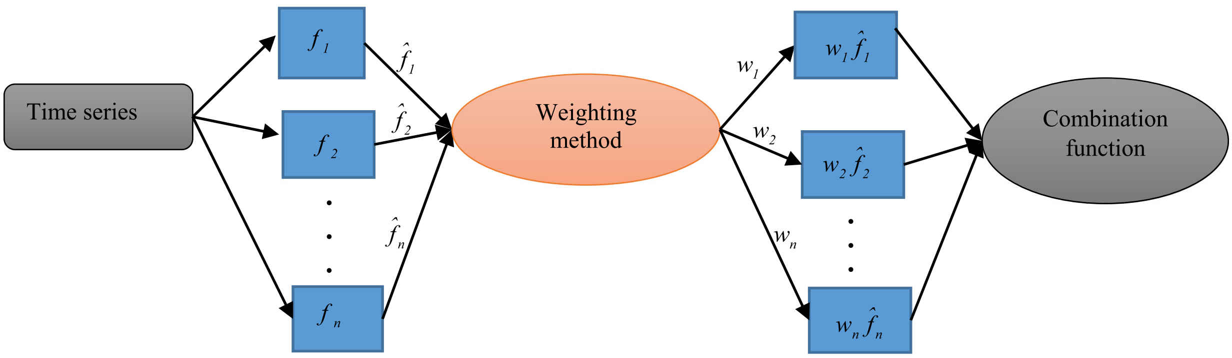

Fig. 2. The general framework of parallel hybrid structure.

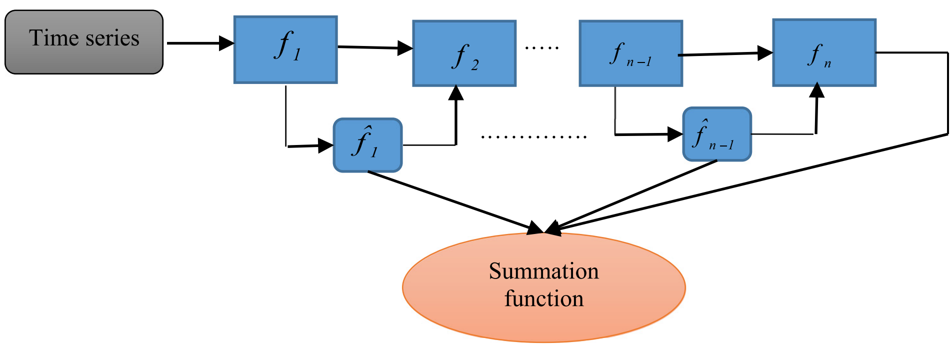

Fig. 3. The general framework of series hybrid structure.

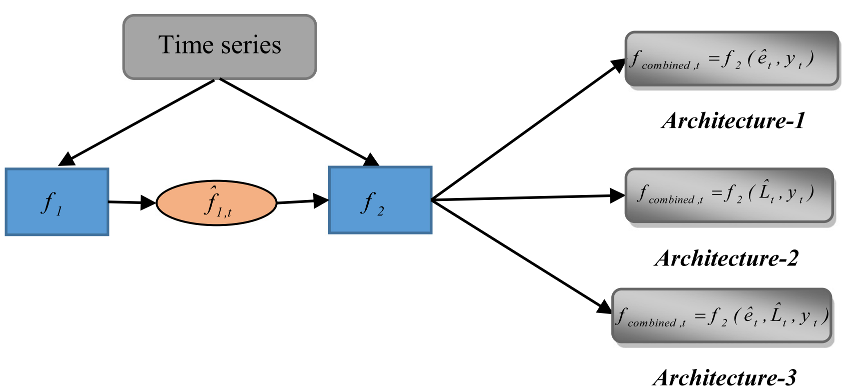

Fig. 4. The general framework of parallel–series hybrid structure.

Table 3
The general information of reviewed papers.

Type of hybrid models	Total paper	Number of Conferences paper	Number of journals paper
Parallel	84	22	62
Series	126	26	100
parallel–series	6	1	5

3.1.1. Linear combination methods

The linear combination method is the most commonly used method for parallel hybridization. In linear combination approach, final combined forecasts are obtained by summation of weighted forecasts of each individual model (Eq. (1)). Thus, the main objective issue in parallel linear hybridization is to determine the appropriate weight for each individual model. Since the primary parallel hybrid scheme proposed by Bates and Granger (1969), Dickinson (1973, 1975), and Newbold and Granger (1974) various essential works have been done for developing weights assignment approaches in parallel hybrid models. As a result, several weighting approaches have been evolved in the literature that can be classified in to two main static and dynamic groups. In this section, papers regarding to each of these weighting approaches are reviewed.

3.1.1.1. Static weighting approaches. In the static weighing approaches, the corresponding weights are estimated by statistical methods and applied for all forecasting horizons. In another word, time is considered as a fixed variable along with weight determining procedure. Static groups are generally divided in to six classes: (1) Averaging, (2) Minimizing error, (3) Var-Cov, (4) Outperformance, (5) DMSFE, and (6) Differential. In such methods, exact values of component weights are calculated through mathematical equations. In the next subsections, a brief description of reviewed papers in each of these statistical methods is presented.

✔ **Averaging method**

It is proven in the literature that averaging different forecasting models can reduce estimation variance (Yin et al., 2012). Although,

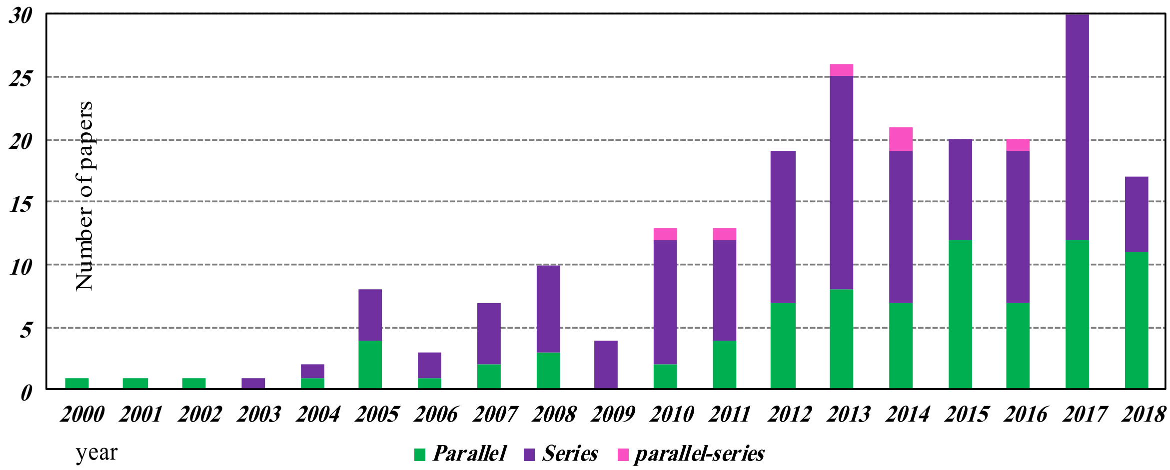

Fig. 5. Depicts the distribution of the reviewed articles regarding to the publication year. It can be seen that the parallel structure is the oldest and parallel–series structure is the newest developed structure. In recent years, the number of studies that incorporates the hybrid structures is generally increased. In addition, the number of papers that used series hybrid structure is overall further than parallel ones. Moreover, in spite of obtaining higher accurate results by utilizing the parallel–series hybrid structure, articles developed in this category are quite limited.

there is a large literature on using averaging multiple forecasting models, there is no consensus about which model averaging should be used. Here, the most cited averaging methods used for weighting individual models in the literature are reviewed.

SA: The SA is the easiest way for determining component weights, which allocated equal weight to each forecasting model. There is some evidence in the literature that simple average method can perform well in terms of accuracy and also in some cases obtain superior performance compared with other advanced methods (Wang et al., 2018b; Genre et al., 2011; de Menezes et al., 2000). SA is used as a main choice of determining weights in parallel models or in comparison with other methods in large amount of studies (See Table 4). Median (Stock and Watson, 2004), TM, and WM (Jose and Winkler, 2008) are robust alternatives to simple averaging. In median method, the median of forecasting results obtained by various individual models is considered as a final hybrid result. The TM and WM weighting methods are formulated in Eqs. (7) and (8), respectively.

$$TM(i) = \frac{1}{n-2i} \sum_{k=i+1}^{n-i} \hat{f}_k \tag{7}$$

$$WM(i) = \frac{1}{n} \left[i\,\hat{f}_{i+1} + \sum_{k=i+1}^{n-i} \hat{f}_k + i\,\hat{f}_{n-i} \right] \tag{8}$$

where, i is the integer and is $0 \leq i \leq {}^{n}\!/_{2}$. The BCM (Finlayson, 2013) method is similar to the SA; however, the sum of forecasts error variance is sorted in BCM method. The weights calculation formula in BCM method is given in Eq. (9)

$$W_i = \frac{c^{i}_{2n-1}}{2^{2n-2}} (i = 0, 1, \dots, n-1) \tag{9}$$

SWAM: The SWAM is the unequal weighted average method (Madigan and Raftery, 1994). This method is also sorts the sum of forecast errors, which is defined in Eq. (10).

$$w_i = \frac{i}{\sum_{i=1}^{n} i} (i = 1, 2, \dots, n) \tag{10}$$

BMA: in this averaging method (Madigan and Raftery, 1994; Hoeting et al., 1999), the weights of individual models are determined regarding to their posterior model probabilities. The Bayesian posterior probabilities for each model are considered as corresponding weights using Bayesian information criteria as given in Eq. (11).

$$w_i = \frac{\exp(-\frac{1}{2} BIC_i)}{\sum_{j=1}^{n} \exp(\frac{-1}{2} BIC_j)}, \qquad BIC_i = m.\ln(\hat{\sigma}_i^2) + k_i.\ln(m) \tag{11}$$

where, $\hat{\sigma}_i^2$ is the estimated error variance of ith model, $k_i$defined as a number of parameters in ith model, and m is the number of observations in time series. In Table 5, the reviewed papers used different averaging weighting methods are listed.

✔ Minimizing error (min error)

In this method, the corresponding weight of each individual model is estimated through minimizing errors between combined forecasts and actual values (Eq. (12)). Different robust mathematical methods and also meta-heuristic algorithms are developed in order to solve this optimization problem. The ordinary least squared method (Granger and Ramanathan, 1984) and simplex are the most cited mathematical methods and genetic algorithms and PSO are frequently used metaheuristic algorithms for solving Eq. (12) addressed in the literature.

$$Min \quad G\left(y_t - \hat{y}_{combined(t)}\right) \qquad t = 1, 2, .., T \tag{12}$$

where, G is a predetermined function such as sum squared (SSE), mean squared (MSE), sum absolute (SAE), mean absolute (MAE), etc., y_t is the actual value, and $\hat{y}_{combined(t)}$ is the obtained forecast at time t. The information of surveyed papers used the Min error approach for estimating weights in linear static parallel combination scheme is summarized Table 6.

✔ Var-Cov method

The basic idea of Var-Cov method proposed by Bates and Granger (1969) is to determine each model weight by minimizing the error variance of the hybrid forecast using the past forecasting performance. Suppose that the final parallel hybridization of two unbiased models is obtained by Eq. (13), in which the sum of weights is equal to one. In this way, the forecasting error can be represented as Eq. (14).

$$y_{combined,t} = w_1 f_{1,t} + w_2 f_{2,t} \qquad \left(w_1 + w_2 = 1\right) \tag{13}$$

$$\begin{aligned} e_{combined,t} &= y_t - \hat{y}_t = \sum_{i=1}^{n} w_i y_t - (w_1 f_{1,t} + w_2 f_{2,t}) \\ &= w_1(y_t - w_1 f_{1,t}) + w_2(y_t - w_2 f_{2,t}) \end{aligned} \tag{14}$$

Therefore, the variance of error term is calculated as follows:

$$var(e_{combined}) = w_1^2 var(e_1) + w_2^2 var(e_2) - 2 w_1 w_2 cov(e_1, e_2) \tag{15}$$

Accordingly, the weights that minimize the variance of error are obtained by following equations:

$$w_1 = \frac{var(e_2) - cov(e_1, e_2)}{e_1^2 + e_2^2 - 2cov(e_1, e_2)} \tag{16}$$

Table 4
Distribution of the papers with respect to forecasting fields.

Forecasting Field	Article(s)	Forecasting Field	Article(s)
Real data	Zhang (2003), Khashei and Bijari (2010, 2011), Wang et al. (2018b), Adhikari and Verma (2016), Adhikari (2015), Adhikari et al. (2015), Adhikari and Agrawal (2013), Adhikari and Agrawal (2012b), Adhikari and Agrawal (2012c), Martins and Werner (2012), Lean et al. (2005), Khairalla et al. (2017), Prudˆencio and Ludermir (2004), Hirata et al. (2015), Khandelwal et al. (2015), McDonald et al. (2013), Wang et al. (2013b), Khashei et al. (2012b), Aladag et al. (2009), Valenzuela et al. (2008), Sarıca et al. (2018), Terui and van Dijk (2002), Adhikari and Agrawal (2012a) and Oliveira and Ludermir (2014)	GDP	Yin et al. (2012), Li and Tkacz (2001), Dongmei et al. (2007) and Qu et al. (2006)
Stock market	Xiong et al. (2015), Haji Rahimi and Khashei (2018), Babikir and Mwambi (2016), Wang et al. (2012), Tarsauliya et al. (2011), Aladag et al. (2010), Mohiuddin Rather et al. (2015), McDonald et al. (2014), Adhikari and Agrawal (2014), Xiong et al. (2017), Khashei and Hajirahimi (2017), Luo and Wang (2017), Hajirahimi and Khashei (2016), Kapi et al. (2015), Kumar and Thenmozhi (2014), Shi et al. (2012b), Zhang et al. (2008), Pai and Lin (2005), Maia and de Carvalho (2011), Barbulescu and Bautu (2012), Khashei and Hajirahimi (2018) and Sallehuddin et al. (2008)	Throughput	Zhou and Zhao (2016), Li et al. (2008), Zhang et al. (2013a), Xie et al. (2013), Mo et al. (2018) and Xiao et al. (2012)
Interest rate	Yu and Zhang (2008)	Solar	Tascikaraoglu et al. (2014), Wu and Chan (2011), Yang and Dong (2018), Gairaa et al. (2016) and Benmouiza and Cheknane (2015)
Bank circulation	Prayoga et al. (2017)	Health	Wang et al. (2013a), Eswaran and Logeswaran (2012a), Xu et al. (2016), Wei et al. (2016), Yu et al. (2014), Ren et al. (2013), Riahi et al. (2013), Joy and Jones (2005), Purwanto et al. (2010) and Wang et al. (2017a)
Oil price and demand	Safari and Davallou (2018), dos Santos and Vellasco (2015), Wang et al. (2018a) and Zhang et al. (2010)	Sales and Demand	Mohammadi et al. (2014), Aburto and Weber (2007), Zhang et al. (2013b), Han et al. (2017), Gurnani et al. (2017) and Liu et al. (2013)
Wind energy, power and speed	Netsanet et al. (2018), Barassi and Zhao (2017), Morina et al. (2016), Li et al. (2011), Drago and Lombardi (2015), Tascikaraoglu et al. (2014), Xiao et al. (2015a), Morina et al. (2017), Shukur and Lee (2015), Ye et al. (2013), Shi et al. (2012a), Cadenas and Rivera (2010), Yuan et al. (2017), Zhang et al. (2012a), Guo et al. (2011), Wang et al. (2015), Chen et al. (2018), Wang and Hu (2015), Lee and Tong (2011) and Xuemei et al. (2009)	Production	Rathod et al. (2017), Khashei et al. (2012a), Sujjaviriyasup (2013) and Yang and Li (2015)
Tourism and passenger	Liu et al. (2017), nor et al. (2017), Cang (2011), Shen et al. (2008), Cang (2013), Ming et al. (2014), Aslanargun et al. (2007), Hakan Aladag et al. (2012) and Chen (2011)	Hot Rolling	Sun et al. (2017a)
Stream flow	Moeeni and Bonakdari (2017b), Wang et al. (2005), Zhou et al. (2018), Pwasong and Sathasivam (2017), Banihabib and Ahmadian (2018) and Moeeni and Bonakdari (2017a)	call arrivals	Barrow (2016)
Traffic flow	Wang et al. (2017b), Li et al. (2017), Ch. Xu et al. (2016), Zeng et al. (2008), Guo et al. (2018) and Tang et al. (2013)	Internet traffic	Katris and Daskalaki (2015)
Exchange rate	Yu et al. (2005), Khairalla et al. (2018), Khairalla and Ning (2017), Lai et al. (2006), Xie et al. (2015b), Ling et al. (2015), Sermpinis et al. (2012) and Xiao et al. (2014), Xiong et al. (2017)	Morbidity, birth Immigration	Eswaran and Logeswaran (2012b)
Weather and pollutant	Haidar and Verma (2017), Saba et al. (2017), Al-Alawi et al. (2008), Dı́áz-Robles et al. (2008), Leng et al. (2017), Wongsathan and Seedadan (2016) and Mahajan et al. (2018)	NN3 competition (NN3)	dos Santos and Vellasco (2015)

(*continued on next page*)

$$w_2 = \frac{var(e_1) - cov(e_1, e_2)}{var(e_1) + var(e_2) - 2cov(e_1, e_2)} \tag{17}$$

Thus, the estimators of previous weights can be represented as follows:

$$w_1 = \frac{e_2^2 - cov(e_1, e_2)}{e_1^2 + e_2^2 - 2cov(e_1, e_2)} \tag{18}$$

$$w_2 = \frac{e_1^2 - cov(e_1, e_2)}{e_1^2 + e_2^2 - 2cov(e_1, e_2)} \tag{19}$$

Most of the studies and also Bates and Granger (1969) have suggested that the weights formulated in Eq. (20) can be used rather than

Table 4 (*continued*).

Forecasting Field	Article(s)	Forecasting Field	Article(s)
Electricity	Jeong et al. (2014), Tian and Hao (2018), Ozozen et al. (2016), Chaâbane (2014), Eswaran and Logeswaran (2012), Yan and Chowdhury (2013), Che and Wang (2010), Fard and Akbari-Zadeh (2014), Mohamed and Ahmad (2010), Mohamed and Ahmad (2008), Lu et al. (2004), Karthika et al. (2017), Pwasong and Sathasivam (2016), Bouzerdoum et al. (2013), Skopal (2015), Shafie-khah et al. (2011), Zhang et al. (2012b), Laouafi et al. (2017), Li et al. (2016), Xie et al. (2015a), Zhao et al. (2014), Xiao et al. (2017), Yang et al. (2016), Xiao et al. (2015b), Wang et al. (2014), Bashari et al. (2014), Kavousi-Fard and Kavousi-Fard (2013) and Nie et al. (2012)	Solid Waste Generation	Song et al. (2014)
Energy consumption	Jovanović et al. (2015), Fan et al. (2014), Barak and Sadegh (2016) and Wang and Meng (2012)	Machine state	Pham et al. (2010)
Computer science	Hsu et al. (2010) and Pati and Shukla (2014)	Property Crime Rates	Alwee et al. (2013)
Rainfall, Drought	Tareghian and Pourreza Bilondi (2013), Mishra et al. (2007), Yan and Ma (2016), Kane and Yusof (2013) and Nourani et al. (2011)	Tidal current	Kavousi-Fard (2017)
Quality	Yin et al. (2016), mer Faruk (2010) and Zhang et al. (2016)	Inspection	Ruiz-Aguilar et al. (2014)
Inflation	Kapetanios et al. (2008) and Öğünç et al. (2013)	Price	Naveena (2017), Mitra and Paul (2017), Zhu and Wei (2013), Koutroumanidis et al. (2009), Shahwan and Odening (2007), Bo et al. (2007), Huang and Wu (2006), Areekul (2010) and Zou et al. (2007)

Table 5
Summary of reviewed papers using Averaging weighting methods.

Ref.	SA	Median	TM	WM	BCM	SWAM	BMA	Ref.	SA	Median	TM	WM	BCM	SWAM	BMA
Wang et al. (2018b)	*	*						dos Santos and Vellasco (2015)	*						
Haji Rahimi and Khashei (2018)	*							Jovanović et al. (2015)	*	*					
Safari and Davallou (2018)	*							Zhao et al. (2014)	*						
Netsanet et al. (2018)	*							McDonald et al. (2014)	*						
Yang and Dong (2018)	*							Adhikari and Agrawal (2013)	*	*	*				
Wang et al. (2018a)	*							Hsu et al. (2010)	*	*					
Haji Rahimi and Khashei (2018)	*							Tareghian and Pourreza Bilondi (2013)	*						
nor et al. (2017)	*							Öğünç et al. (2013)	*	*	*				
Zhou et al. (2018)	*							Adhikari and Agrawal (2012c)	*	*	*				
Guo et al. (2018)	*							Wang et al. (2012)	*						
Tian and Hao (2018)	*							Yin et al. (2012)	*				*		
Laouafi et al. (2017)	*		*				*	Sermpinis et al. (2012)	*				*		
Haidar and Verma (2017)	*		*					Martins and Werner (2012)	*						
Hajirahimi and Khashei (2016)	*							Adhikari and Agrawal (2012b)	*	*					
Barassi and Zhao (2017)	*						*	Li et al. (2011)					*		
Saba et al. (2017)	*							Cang (2011)	*						
Yin et al. (2016)	*				*			Tarsauliya et al. (2011)	*						
Adhikari and Verma (2016)	*		*					Drago and Lombardi (2015)	*						
Morina et al. (2016)	*							Aladag et al. (2010)	*						
Babikir and Mwambi (2016)	*							Kapetanios et al. (2008)	*						
Li et al. (2016)	*							Shen et al. (2008)	*						
Adhikari (2015)	*	*						Zou et al. (2007)	*						
Xie et al. (2015b)	*							Yu et al. (2005)	*						
Ling et al. (2015)	*							Wang et al. (2005)	*						
Fan et al. (2014)	*		*	*				Lean et al. (2005)	*						
Xie et al. (2015a)	*							Prudˆencio and Ludermir (2004)	*						
Li and Tkacz (2001)	*							Adhikari and Agrawal (2012a)	*						

Eqs. (18) and (19).

$$w_1 = \frac{e_2^2}{e_1^2 + e_2^2}, \quad w_2 = \frac{e_1^2}{e_1^2 + e_2^2} \tag{20}$$

In the similar fashion, corresponding weights for combining the multiple cases can be presented by the following equation (Fritz et al., 1984).

$$w_i = \left[\sum_{j=1}^{T} {e_{j,i}}^2\right]^{-1} \Bigg/ \sum_{i=1}^{n}\left[\sum_{j=1}^{T} {e_{j,i}}^2\right]^{-1} \tag{21}$$

where, the e_i is the obtained error that can be different kinds of forecasting error and n denotes the number of individual based involved models. Various hybrid models have used the Var-Cov weighting method for constructing parallel hybrid structure for time series forecasting [See Table 7]. It is must be noted that in some papers, this approach is also called error based weighting method.

✔ Outperformance

This weighting method was first proposed by Bunn (1975) on the basic concept of Bayesian probabilistic approach. In this method, the related weight of each single model is determined based on the number

Table 6
Summary of reviewed papers using Min error weighting method.

Article	Year	Error type	Solution method	Constructive models
Haji Rahimi and Khashei (2018)	2018	SSE	OLS, GA	ARIMA, MLP
Yang and Dong (2018)	2018	SSE, SAE	OLS, LAD, CLS	SARIMA, MLP, STL, TBATS, theta model
Netsanet et al. (2018)	2018	SSE	OLS	MLP, ANFIS, SVM, RBFNN
Safari and Davallou (2018)	2018	NA	GA	ARIMA, NAR, ESM
Sarıca et al. (2018)	2018	NA	GCPSO	AR, ANFIS
Wang et al. (2018b)	2018	SSE	OLS	MLP, DAN2, ELNN, ESN
Khairalla et al. (2017)	2017	SSE	OLS	ARIMA, MLP, EXP
Khairalla et al. (2018)	2018	SSE	OLS	ARIMA, EX, MLP
Khashei and Hajirahimi (2017)	2017	SSE	GA, OLS	ARIMA, MLP
Xiao et al. (2017)	2017	SSE	(MOFPA)	MLP, GABPNN, WNN, RBFNN and GRNN
Barassi and Zhao (2017)	2017	MSE	OLS	NAR, VAR
Hajirahimi and Khashei (2016)	2016	SSE	OLS	ARIMA, MLP
Yang et al. (2016)	2016	NA	DE	MLP, ANFIS, SARIMA
Adhikari and Verma (2016)	2016	SSE	OLS	RW, SVM, MLP, ELNN, GRNN, LSSVM
Zhou and Zhao (2016)	2016	SSE	NA	SARIMA, LSSVM
Yin et al. (2016)	2016	SSE, SAE, MMAE	NA	PCR, PLSR, MPLSR
Babikir and Mwambi (2016)	2016	NA	SAA	Chaotic, ANN PLS-SVM model
Li et al. (2016)	2016	NA	IA-PSO	Para-curve model, GM, EXP, Hyperbola model, Logarithm model
Xiao et al. (2015a)	2015	SSE	GA–CM–NNCT, PSO–CM–NNCT	ARIMA, ARCH, SVM, MLP, KF
Xiao et al. (2015b)	2015	Absolute error	Cuckoo algorithm	MLP, RBFNN, GRNN, ANN with double hidden layers, GABPNN
Adhikari (2015)	2015	SSE	OLS	Box–Jenkins SVM, MLP, ELNN
Mohiuddin Rather et al. (2015)	2015	MSE	GA	ARIMA, RNN, ESM
Song et al. (2014)	2014	–	SAA	Chaotic model, ANN, SVM
Fan et al. (2014)	2014	MAPE	GA	MLR, SVR, RF, MLP, BT, MARS, KNN., ARIMA
Tascikaraoglu et al. (2014)	2014	SSE	pseudoinverse technique	EMD-CFNN, Linear model
Zhao et al. (2014)	2014	SSE	NA	PSTM, PTTM, HWM
Adhikari and Agrawal (2013)	2013	SSE	OLS	ELNN, ARIMA, SVM, MLP
Zhang et al. (2013a)	2013	MSE	Nonlinear programming	Logistic-growth-curve model, GM
Liu et al. (2013)	2013	NA	SAA	Adaptive ESM, MA, HWM, ESM with trend
Tareghian and Pourreza Bilondi (2013)	2013	MSE	OLS	SLM, LPM, LVGFM
Adhikari and Agrawal (2012c)	2012	SSE	OLS	ELM, SVM, LSSVM, ARIMA
Wang et al. (2012)	2012	NA	GA algorithm	ARIMA, ESM, MLP
Adhikari and Agrawal (2012a)	2012	SSE	OLS	ARIMA, ANN, EANN
Sermpinis et al. (2012)	2012	Squared error	LASSO, Granger and Ramanathan Regression	MLP, RNN, PSNN
Zhang et al. (2010)	2010	Absolute error, relative error	conventional mathematical methods	gray GM (1,1) model, Residual error gray model, Dynamic fill-dimensional gray model
Dongmei et al. (2007)	2007	SSE	Nonlinear programming	MLR, EXP, ARIMA
Lai et al. (2006)	2006	MAE	Simplex algorithm	ESM, MLP
Yu et al. (2005)	2005	Absolute error	Simplex algorithm	GLAR, MLP
Lean et al. (2005)	2005	error-variance	Quadratic programming	ARIMA, ESM, SMA and ANN
Wang et al. (2005)	2005	MSE	OLS	ARMA, PAR, MLP, PANN
Terui and van Dijk (2002)	2002	SSE	OLS	TAR, EXP TAR
Li and Tkacz (2001)	2001	NA	OLS, NRLS, ERLS, WLSP	RW, ES

of times that the specific single model represents the best performance in the past in sample forecasting trials (Netsanet et al., 2018).

✔ DMSFE

Winkler and Markakis (1983) have suggested the DMSFE method for determining weights in parallel hybrid models, which is calculated as Eq. (22).

$$w_i = \frac{\left[\sum_{j=1}^{T}(\delta^{T-j+1}e_{j,i}^2)\right]^{-1}}{\sum_{i=1}^{n}\left[\sum_{j=1}^{T}(\delta^{T-j+1}e_{j,i}^2)\right]^{-1}} \quad \sum_{i=1}^{n} w_i = 1 \tag{22}$$

where, δ is referred to discount factor with $0 < \delta \leq 1$. It should be noted that the Var-Cov method is specific case of the DMSFE, if $\delta = 1$. The calculated weights by the DMSFE method satisfied the constraint $\sum_{i=1}^{n} w_i = 1$.

✔ Differential

As mentioned previously, in the Var-Cov method, the information of covariance matrix is required to be minimized the variance of hybrid forecast error, which is practically unknown. Due to this limitation (Newbold and Granger, 1974; Makridakis and Winkler, 1983), differential methods have been proposed in the literature. These methods can be generally categorized in five classes, which two most frequently used types of them are presented in Eqs. (23) and (24).

$$w_i = \left(\sum_{s=t-v}^{t-1}(e_{i,s})^2\right)^{-1} \Bigg/ \sum_{j=1}^{n}\left(\sum_{s=t-v}^{t-1}(e_{j,s})^2\right)^{-1}$$
$$(i = 1,2,\dots,n)(t = 1,2,\dots,T) \tag{23}$$

$$w_{i,t} = \beta w_{i,t-1} + (1-\beta)\frac{\left(\sum_{s=t-v}^{t-1}(e_{i,s})^2\right)^{-1}}{\sum_{j=1}^{n}\left(\sum_{s=t-v}^{t-1}(e_{j,s})^2\right)^{-1}}$$
$$(i = 1,2,\dots,n)(t = 1,2,\dots,T) \tag{24}$$

where, ν and β are two constant parameters in which $0 < \beta \leq 1$ and e_{it} is the percentage error at time t, which is calculated by Eq. (25).

$$e_{i,t} = \frac{y_t - \hat{y}_{it}}{y_t} \qquad (i = 1, 2, \ldots, n)(t = 1, 2,.., m) \tag{25}$$

The reviewed articles applied the Var-Cov, the outperformance, the DMSFE and the Differential weighting methods for constructing parallel hybrid models are summarized in Table 7.

3.1.2. Dynamic weighting approaches

Although, statics weighting approaches are the much more cited methods in the literature in which each component weight is determined based on the historical data and applied over the whole of forecast horizon or during the time, some dynamic weight generation schemes are also proposed for overcoming the deficiency of this method related to lacking the flexible method for updating information during the time. In the dynamic weighting methods, the component weights varied with each time index (Yang, 2004; Sánchez, 2008). It is documented in the literature that there is no guarantee that dynamic combination models can always outperform astatic ones, but some dynamic combination schemes can often improve forecasting performance (Timmermann, 2006). The brief description of each dynamic weighting method used in literature is given here.

Wang et al. (2018b) have presented a parallel forecast combination model by integrating four kinds of neural networks. In this study, a dynamic weighting procedure called in-sample training–validation pair-based neural network (TVPNNW) is applied for obtaining the weight of components. Simulation results indicate that the proposed model shows better performance than some static combination methods such as SA, Median, OLS, Outperformance, and Var-Cov methods. Adhikari (2015) has worked on a linear parallel combination system in which the hybrid weights are determined by a novel dynamic method. In this study, weights are assigned to Box–Jenkins, SVM, MLP and ELNN components with static Var-Cov method. Then, an ANN model is employed to discover and learn inherent patterns of in-sample weights. The findings confirm that the proposed model can yield more accurate forecasting results, compared with its based components as well as other well recognized linear static combination approaches.

Zhao et al. (2014) have suggested a time-varying weighted average method for parallel hybridization of SARIMA, MLP, and LSSVR. In the proposed model, at the first step, an in-sample time-varying combining weights for each component are calculated with quadratic programming. Then, the out-of-sample dynamic weights predicted by these in-sample weights employing a high order Markov chain model. Evaluation results point out that the proposed dynamic hybrid model outperforms its components and some traditional static approaches. Reviewed papers used parallel hybrid models by employing dynamic weighting approaches are summarized in Table 8.

3.2. Nonlinear combination methods

The straightforward alternative for parallel hybridization is to use the linear combination function, which is described in the previous section. However, in parallel hybrid models, the linear integration approaches will be generally unsatisfactory, if the true relationship is nonlinear. While, the assumption of linear function for data generation process of components in real world problems is often nonlinear. For this reason, the nonlinear combination functions have been proposed in the literature for addressing this problem. In earlier studies, ANNs are applied in order to discover the nonlinear relationships among forecasting outputs (Shi et al., 1999). In general, the parallel nonlinear combination can be developed in two main frameworks. The first option is to mathematically use the correlation among components in order to lift the limitation of the linear combination framework for modeling interconnection patterns. The combined forecast for integrating three individual models, as an example, is given in Eq. (26).

$$y_{combined,t} = w_0 + w_1 \hat{f}_{1,t} + w_2 \hat{f}_{2,t} + w_3 \hat{f}_{3,t} + \theta_1 v_{1,t} v_{2,t} + \theta_2 v_{2,t} v_{3,t} + \theta_3 v_{3,t} v_{1,t} \tag{26}$$

where, $v_{i,t} = \frac{(y_{t,i} - \mu_i)}{(\sigma_i)^2} \quad (i = 1, 2, 3)(t = 1, 2, \ldots, T)$, μ_i and σ_i are the mean and standard deviation of the $\hat{f}_i$, respectively. In this scheme, the weights are calculated by solving the optimization problem regarding to minimizing corresponding forecasting errors such as SSE. The presented mathematical procedure of this matter can be followed in Adhikari and Agrawal (2012b,a), Xie et al. (2015b).

Second option consists of applying intelligent models to obtain corresponding weights and nonlinear combination function, concurrently. In contrast to linear combination framework, in this framework, the weight of each model is calculated during the processing procedure of intelligent model and is not predetermined. Therefore, the output of intelligent model is considered as final hybrid result. The advantage of this method is that the historical data is used in order to determine component weights. In research works done in combining multiple models with parallel hybrid concept, different kinds of intelligent models are employed to combine individual models, component weights, and hybrid outputs. The information of related articles in which intelligent models are used as parallel nonlinear combination is given in Table 9.

3.3. Summary of parallel reviewed models

The distribution of analyzed parallel models regarding to combination function and weighting methods is shown in Fig. 6. From the reviewing 84 papers, the following points can be concluded:

(1) Among linear hybrid combination methods, static ones are most cited methods. However, dynamic based parallel hybrid models obtain more accurate results compared with static ones (Table 7).
(2) As seen in Fig. 6, the most widely used static weighting methods are averaging and Min error, with 34% and 26% of the papers, respectively.
(3) In spite of the frequently used linear hybrid models, only a few studies addressed nonlinear combination approaches. However, the reviewed papers showed that more satisfactory results can be obtained using nonlinear combined models in comparison with linear ones (Table 9).
(4) Empirical results obtained by different approaches in the min error weighting category verify that, mathematical methods e.g. OLS can obtain better performance with lower computational cost against meta heuristic algorithms.
(5) Based on the existing confirmations provided in the literature, improved forecasting accuracy can be usually yielded by using parallel hybridization compared with individual models.
(6) According to the theoretical evidences, the risk of using inappropriate individual models will be reduced by parallel combination of different components.

4. Reviewing series hybrid structure in time series forecasting

Research and development on hybrid models has grown dramatically since 2003, which series structure and method is proposed by Zhang (2003). Since then, most of the articles have been focused on the series models for extracting unique merits of different individual models in sequential modeling in order to get superior performance compared with individual base models, in wide variety of real world modeling and forecasting problems. In this section, the series models are reviewed based on the sequence of modeling, i.e. the most specific characteristic of this structure.

Table 7
Reviewed papers using Var-Cov, outperformance, DMSFE, and Differential weighting methods.

Article	Var-Cov	Out-performance	DMSFE	Differential	Article	Var-Cov	Out-performance	DMSFE	Differential
Wang et al. (2014)	*								
Wang et al. (2018b)	*	*			Yang and Li (2015)	*			
Zhou et al. (2018)	*				Adhikari et al. (2015)	*			
Wang et al. (2018a)			*		Laouafi et al. (2017)	*			
Netsanet et al. (2018)		*			Adhikari and Agrawal (2012b)	*			
Guo et al. (2018)	*				Adhikari and Agrawal (2013)		*		
Leng et al. (2017)	*				Hsu et al. (2010)	*			
Liu et al. (2017)	*				Cang (2013)	*		*	
Khairalla and Ning (2017)	*				Wang et al. (2013a)	*			
Laouafi et al. (2017)	*				Yin et al. (2012)	*			
Adhikari and Verma (2016)	*				Martins and Werner (2012)	*			
Babikir and Mwambi (2016)	*		*		Adhikari and Agrawal (2012c)	*	*		*
Adhikari (2015)	*	*			Cang (2011)	*		*	
dos Santos and Vellasco (2015)	*				Shen et al. (2008)	*		*	

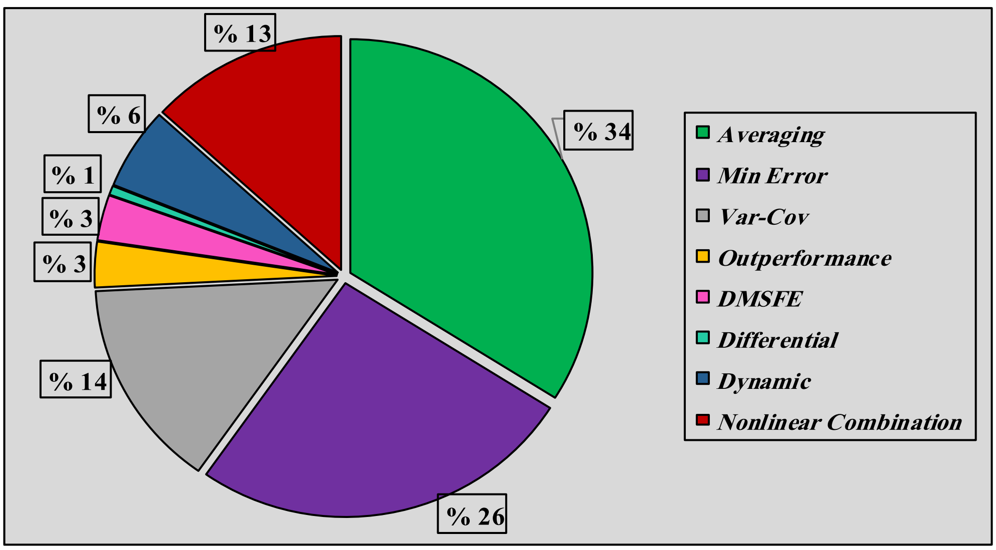

Fig. 6. Distribution parallel hybrid models included in the review.

Table 8
Summary of reviewed papers using dynamic weighting methods.

Ref.	Dynamic weighting method	Compared with	Obtained results
Safari and Davallou (2018)	State space and Kalman filter model	Constructive ARIMA, NAR and ESM models, the SA and min error solved by GA static based hybrid models, the series ARIMA-ANN hybrid model	The numerical results showed a decrease in forecasting error using the dynamic weighting approaches.
dos Santos and Vellasco (2015)	Neural Expert Weighting (NEW)	SA and Var-Cov weighting methods	The dynamic proposed framework can enhanced the forecasting accuracy compared with traditional static algorithms.
Bashari et al. (2014)	Kalman fusion algorithm	ANFIS, ANN, ARMA	The hybrid model yield more accurate results.
Sermpinis et al. (2012)	Time-varying leverage with Kalman Filter	Other static combination methods SA, BMA, Granger–Ramanathan's Regression Approach (Granger and Ramanathan, 1984) and the LASSO.	The proposed Kalman filter based hybrid model performed in an optimal way for forecasting the under study time series compare with other static based hybrid models.
Lean et al. (2005)	Time varying minimum-squared error	ARIMA, ESM, SMA and ANN, SA, min error static methods and nonlinear combination method	The nonlinear parallel hybrid model can be used as a proper alternative for obtaining more accurate result.
Terui and van Dijk (2002)	Time varying regression	Constant combined static based model, linear, TAR and an Exp. AR individual models	The hybrid models in two constant and time-varying schemes perform well, especially with time varying coefficients.

Hybrid series models that decompose time series in to linear and nonlinear components have shown suitable performance because of those mixture patterns existed in most of the real world data. Therefore, based on two sequence modeling procedure, i.e. linear–nonlinear or nonlinear–linear, two types of series models are developed in the literature. In the literature, numerous statistical and intelligent models have been used for constructing series models due to their specific features in linear and nonlinear patterns recognition. This section covers the articles employed series models from 2003 to 2018 in time series modeling and forecasting domains. The description of these two series hybrid models is also given in the following subsections.

4.1. Linear–nonlinear sequential modeling

Various hybrid models addressed in the literature follows the linear–nonlinear modeling procedure when linearity and nonlinearity of patterns in unknown. Therefore, by selecting the statistical models as first permutation and intelligent model as second one, various series models

Table 9
Summary of reviewed papers using nonlinear combination functions.

Ref.	Combination function	Compared with	Obtained results
Tian and Hao (2018)	Modified SVM	Two linear combined models such as SA and entropy weight based combined model	The proposed nonlinear combination method performs accurately.
Guo et al. (2018)	KNN	SA and Var-Cov based combined model, ANN, SVR, RF	Simulation results show that while the accuracy of the SA and Var-Cov hybrid models is comparable to the accuracy of individual methods, the KNN based method can achieve significantly superior results
Zhou et al. (2018)	GRNN	SA and Var-Cov based combined model, ELNN, RFB, ELM	Nonlinear GRNN based models performed better than other linear combined models and also its components
Chen et al. (2018)	SVRM	Popular individual forecasting models such as ARIMA, SVR, ANN and GBRT	Experimental results compared with other popular prediction models demonstrated that proposed hybrid model can achieve better forecasting performance.
Han et al. (2017)	ANN, SVM	ANN and SVM individual based components	The results show that the Hybrid nonlinear forecasting model is more accurate than the individual forecasting models
Zhou and Zhao (2016)	GP and OLS estimation	Minimize error based hybrid model, ANN based hybrid model SARIMA, LSSVM	The proposed model based on GPLS has a great potential to be a powerful nonlinearly combine forecasting approach
Babikir and Mwambi (2016)	ANN	Var-Cov, DMSFE based hybrid models, dynamic factor and MLP models	The nonlinear ANN combining method also outperforms the best individual forecasting models and also used linear combination methods
Wang and Hu (2015)	GPR	EWT-ARIMA, EWT-LSSVM, ARIMA, SVM, LSSVM	The proposed nonlinear combination method can generate a more reliable and accurate forecast
Tareghian and Pourreza Bilondi (2013)	(FSM), ANN, ANFIS	SA, min error based hybrid models	ANFIS combination method performs better than other hybrid models
Cang (2013)	MLP, SVR and RBF	Var-Cov and MSFE static based hybrid models	Proposed nonlinear combination models are outperformed the linear hybrid models
Cang (2011)	ANN	SA, Var-Cov, and DMSFE static hybrid based models	The empirical results show that the proposed nonlinear combination model is robust, powerful and can provide better performance than linear combination models
Drago and Lombardi (2015)	ANN	SA and Weighted average static based combined models, MLR, MLP, SVM	Three presented parallel hybrid models make improvement in performance of individual models
Aladag et al. (2010)	MLP	SA, MSFE and Var-Cov static based hybrid models	As a result of the implementation, it is confirmed that the proposed nonlinear forecast combination approach produces better forecasts than other linear ones.
Li et al. (2008)	ELNN	SA static based hybrid model, ESM	Proposed hybrid model has a higher forecasting accuracy than based components.
Dongmei et al. (2007)	ANN	MLR, ESM, ARIMA, Var-Cov static based combined model	The nonlinear ANN based hybrid model represent more accurate forecasting result.
Lean et al. (2005)	ANN	SA and min error static based hybrid model, time varying min error dynamic based hybrid models, ARIMA, ESM, SMA and ANN	The hybrid models generally perform better than single models. However, the forecasting accuracy of nonlinear hybrid model is better than of linear combined models.
Yu et al. (2005)	PCA+ANN	Series models, SA and min error linear static based hybrid models	The findings reveal that the nonlinear hybrid model can be a good alternative.
Li and Tkacz (2001)	ANN with polynomial weights	SA, min error solved by OLS methods based models static	The result demonstrated that the nonlinear combined forecast outperformed linear hybrid models.
Palit and Popovic (2000)	ANN, fuzzy logic, neuro fuzzy technology	ARIMA, HWM ESM	The non-linear combination of a group of forecasts based on intelligent approach is capable of producing a single better forecast than any individual forecasts involved in the combination.

can be evolved. The linear–nonlinear series models based on the use of different statistical models such as different kinds of ARIMA models (e.g. ARIMAX, SARIMA, etc.) models and intelligent models such as ANN, SVM can be generally divided in to five main groups: (1) ARIMA-ANN (2) ARIMA-SVM (3) ARIMA based model (4) ANN based model (5) SVM based model.

✔ ARIMA-ANN series hybrid models

Focusing on the constructing hybrid models with employing ARIMA and ANN models have experienced enormous attention in published papers in hybrid time series forecasting, specifying in series hybrid models. This popularity comes from specific features of these models in linear and nonlinear modeling. ARIMA is a statistical methodology that predicts future value of data by extracting linear relationship and processing historical data. Neural networks are the most effective group of intelligent models for nonlinear pattern recognition, which are the data driven and universal approximators. Various series models have been developed in the literature by using different kinds of ARIMA and ANN models as components of series hybrid model, which are reported in Table 10. Brief description of some recent studies is given here.

Banihabib and Ahmadian (2018) have proposed a series model by integrating MARIMA model with NARX neural network to enhance forecasting accuracy of monthly inflow forecasting. Authors conclude that in comparison with the ARIMA model, a significant improvement is obtained by combining MARIMA and NARX for flow forecasting due to existing both linear and nonlinear patterns in data. Mo et al. (2018) have presented a four-step series model for container throughput forecasting. This series hybrid model decomposes a time series in two linear and nonlinear parts. Then, in a first step, linear patterns are modeled by SARIMA model. In second stage, three intelligent models including: SVR, MLP and GP are employed in order to forecast the nonlinear remained relationships in SARIMA's residuals. In this paper, the

GMDH neural network is suggested for selecting the appropriate nonlinear forecasting. In the last step, by integrating linear and nonlinear forecasting results, final combined forecasts are calculated. Empirical results of this paper show that the proposed series model based on SARIMA and GMDH neural network produced better performance that SARIMA and other series models such as SARIMA-SVR, SARIMA-GP, and SARIMA-BP for container throughput forecasting.

Sun et al. (2017a) have investigated a series model by combining RARIMA and MLP models for short term forecasting of strip thickness. Obtained results indicate that considerable improvement in terms of accuracy and stability can be yielded by applying hybrid model. Barrow (2016) has proposed a SMA-ANN hybrid model for call arrival forecasting. In this study, two linear AR and nonlinear MLP models are adjusted for modeling remained residuals of the SMA model. This is the first study through SMA evaluation across averages of different lengths for forecasting call arrival data. Results indicate that the SMA-MLP hybrid model found to be more robust than other alternatives, which fits a linear AR model for modeling nonlinear patterns in residuals.

✔ ARIMA-SVM series hybrid models

In some papers, the SVM is chosen as intelligent model in second permutation of the series model due to the merit of this kind of models in solving nonlinear regression estimation. The information of papers employed series ARIMA-SVM models for time series modeling and forecasting is given in Table 11. Another discussed issue in some of these papers is concerned to comparing the ARIMA-ANN models with the ARIMA-SVM series hybrid models. It is clarified in these studies that the ARIMA-SVM models can generally achieve more accurate results (Shi et al., 2012a; Yuan et al., 2017; Zhang et al., 2012b; Rathod et al., 2017).

✔ ARIMA based models

Various ARIMA-based series models proposed in the literature for time series prediction. In these hybrid models, the ARIMA model is selected as first permutation of hybrid model for linear modeling and second model is chosen among other intelligent models, except ANN and SVM models. A brief description of these hybrid series models are given as follows:

Lee and Tong (2011) have proposed a hybrid series model by combining ARIMA and GP models to improve both ARIMA and GP models. They state that the GP model is used rather than MLPs due to their limitations in explanation of the hidden layer. Besides, they claim that by employing the GP model for nonlinear modeling in second step of the proposed model, a mathematical equation can be also obtained. They evaluate the effectiveness of their proposed model in forecasting real data sets in comparison with the ARIMA-ANN, the ARIMA-SVM, and also its constitutes. Kane and Yusof (2013) have presented a hybrid ARFIMA-GARCH model for rainfall forecasting. In this study, the ARFIMA model is employed in order to model the linear relationships. Therefore, residuals obtained by the ARFIMA model consist of heteroskedasticity as a nonlinear relationship, which are processed by the GARCH model in second step. They conclude that the proposed model can be a viable alternative for analyzing both linear and nonlinear behaviors in rainfall time series. The reviewed papers in the ARIMA-based hybrid fields are summarized in Table 12.

✔ ANN based models

ANN based models are basically proposed in the literature in order to address the problem of mixed patterns in data, by using the nonlinear ANN models in second modeling procedure. In Table 13, ANN based series hybrid models, in which the ARIMA model is not used for linear modeling in a first step is presented. Some of these studied are also briefly described here.

Bo et al. (2007) have proposed a hybrid model, incorporating ARCH family models and ANN model. Authors state that according to ARCH theory, the LM test is done and the ARCH effect is detected in data. Thus, at the first state for implementing linear modeling procedure, ARCH family is used and then using the ANN model, residuals of ARCH model are forecasted. Empirical outcomes of this paper indicate that the hybrid ARCH (1)-M-ANN outperforms the ARIMA, ARCH (1), GARCH (1,1), EGARCH (1,1), and ARIMA-ANN Series hybrid model.

Pwasong and Sathasivam (2016) have combined the QRM and CFBN models together in series structure in order to construct the QRM-CFBN hybrid model. Obtained results from comparison of this model with other single and hybrid models, such as CFBN, LRNN, and ARIMA-ANN in forecasting daily time series datasets, obtained from the UCI repository data link and the cycle power plant; indicate that the proposed model can averagely produce better performance than others.

✔ SVM based model

Integration of SVM family models with other linear models, except ARIMA model has highlighted in few studies. Chen (2011) has combined linear models, such as ESM and ARIMA models with two MLP and SVR nonlinear models and proposes four ES-MLP, ES-SVR, ARIMA-SVR, and ARIMA-MLP models. They show that the SVR based hybrid models can achieve good forecasting accuracy and excellent directional change detection in real time series forecasting. The brief information about the SVM based papers are summarized in Table 14.

4.2. Nonlinear–linear sequential modeling

Despite the importance of sequence of components in series hybrid models on the forecast accuracy, only a few studies have addressed the nonlinear–linear series hybrid models. The information related to these papers is summarized in Table 15.

Alwee et al. (2013) have created a series PSOSVR-PSOARIMA hybrid model that are combined the nonlinear SVR model with linear ARIMA model in nonlinear–linear modeling order in series hybrid structure. Empirical results indicate that the proposed model produces smaller forecasting errors in comparison with individual models and PSOSVR-ARIMA series hybrid model. Wang et al. (2015) have proposed a series nonlinear–linear series model, combined ELM and SARIMA models. In this study, the ELM is chosen for extracting nonlinear behaviors of time series in a first stage, due to its merits over ANN models e.g. time-saving and turning — tree features and then SARIMA model is employed for further processing of ELM's residuals. Obtained result of using the proposed hybrid model for wind speed forecasting verify that the proposed hybrid model can yield superior performance in comparison with its based components and also other popular models, such as ARIMA and ANN models.

Another issue in series hybrid models is related to comparing these two types of series models and analyzing the forecasting accuracy in these models. There are limited studies that pay attention both sequence modeling procedures, simultaneously and make a comparison between these two types of series models. Khashei and Hajirahimi (2018) have tried to make complete assessment of two possible types of series models, constructed with ARIMA and ANN models for stock price forecasting. Their empirical results of forecasting three benchmark data sets indicate that despite more popularity of the conventional ARIMA-ANN model, the ANN-ARIMA series hybrid model can overall achieve more accurate results. Purwanto et al. (2010) have proposed two linear–nonlinear and nonlinear–linear series models by combining ARIMA and ANN models. Empirical results of this study indicate that the series hybrid ARIMA-ANN model gives the best performance compared with linear models, ANN and ANN-ARIMA.

Sallehuddin et al. (2008) have presented a study in order to develop a nonlinear–linear series model entitled GRANN-ARIMA. For assessing the performance of proposed GRANN-ARIMA model, the extensive comparison is done with individual ANN, LR, and ARIMA models and also ARIMA-ANN hybrid model. Their experiments indicate that the proposed hybrid model outperforms other models with 99.5% forecasting accuracy for small-scale data and 99.84% for large-scale data. Che and Wang (2010) have represented a combined model using SVR and ARIMA in order to exploit their unique advantages of these models in nonlinear and linear modeling, respectively. Their proposed series model is constructed based on the nonlinear–linear modeling procedure. Obtained results indicate that the proposed SVR-ARIMA model outperforms its based components, ANN, ANN-ARIMA, and ARIMA-SVR hybrid models.

Table 10
Summary of reviewed papers using ARIMA-ANN series models.

Article	Year	Type of ARIMA model	Type of ANN model	Compared with	Superior model(s)
Banihabib and Ahmadian (2018)	2018	MARIMA	NARX	ARMA	ARIMA-NARX
Mo et al. (2018)	2018	SARIMA	GMDH, MLP	SARIMA-MLP, SARIMA-SVR, SARIMA-GP, SARIMA	GMDH based hybrid model
Khairalla et al. (2018)	2018	ARIMA	MLP	Parallel models, ARIMA-MLP, EX-MLP, ARIMA, MLP, EX	Parallel hybrid model
Mahajan et al. (2018)	2018	ARIMA	NNAR	Grid based clustering method ARIMA-NAR	Wavelet based clustering ARIMA-NAR
Safari and Davallou (2018)	2018	ARIMA	MLP	ARIMA, NAR, ESM, parallel hybrid models	Proposed parallel hybrid model
Khashei and Hajirahimi (2017)	2017	ARIMA	MLP	Parallel hybrid models	Both series ARIMA-ANN and ANN-ARIMA models
Li et al. (2017)	2017	ARIMA	RBFNN	ARIMA, RBFNN	ARIMA-RBFNN
Naveena (2017)	2017	ARIMA	MLP	ARIMA, MLP	ARIMA-MLP
Morina et al. (2017)	2017	ARIMA	MLP	ARIMA, MLP	ARIMA-MLP
Prayoga et al. (2017)	2017	ARIMAX	MLP	ARIMAX	ARIMAX-MLP
Sun et al. (2017a)	2017	RARIMA	MLP	ARIMA, RARIMA, MLP	RARIMA–MLP
Khairalla et al. (2017)	2017	EXP	MLP	Parallel model	Proposed linear hybrid model
Rathod et al. (2017)	2017	ARIMA	TDNN	ARIMA, TDNN, NLSVR, ARIMA-NLSVR	ARIMA-NLSVR
Luo and Wang (2017)	2017	ARIMA	MLP	MLP, MLP-PCA	PCA-ARIMA-MLP
Mitra and Paul (2017)	2017	ARIMA	MLP	ARIMA, GARCH	ARIMA-GARCH, ARIMA-MLP
Gurnani et al. (2017)	2017	ARIMA	ARNN	ARIMA-XGBoost, ARIMA-SVM, ARIMA, ARNN, SVR, STL Decomposition	STL Decomposition (using ARIMA, Snaive, XGBoost)
Wang et al. (2017a)	2017	ARIMA	NAR	ARIMA	ARIMA-NAR
Moeeni and Bonakdari (2017a)	2017	SARIMA	MLP	SARIMA, MLP	SARIMA-MLP
Xu et al. (2016)	2016	ARIMA	ANN	LR, ARIMAX, ARIMA-LR	ARIMA-LR
Barak and Sadegh (2016)	2016	ARIMA	ANFIS	ARIMA, MLP, ARIMA-MLP	ARIMA-ANFIS
Wei et al. (2016)	2016	ARIMA	GRNN	ARIMA, GRNN	ARIMA-GRNN
Hajirahimi and Khashei (2016)	2016	ARIMA	ANN	ARIMA, ANN	Both ARIMA-ANN and ANN-ARIMA
Barrow (2016)	2016	SMA	MLP	SMA, MLP	SMA-MLP
Zhang et al. (2016)	2016	ARIMA	RBFNN	ARIMA, RBFNN	ARIMA-RBFNN
Gairaa et al. (2016)	2016	ARIMA	MLP	ARIMA, MLP, NNARX, ELNN, ANFIS, SVR-RBF, SVR-poly	ARIMA-MLP
Ozozen et al. (2016)	2016	SARIMA	MLP	SARIMA	SARIMA-MLP
Yan and Ma (2016)	2016	ARIMA	RBFNN	ARIMA, RBFNN	ARIMA-RBFNN
Katris and Daskalaki (2015)	2015	ARFIMA	MLP, RBFNN	ARFIMA, MLP, RBFNN	AFIMA-MLP, ARFIMA-RBFNN
Kapi et al. (2015)	2015	ARIMA	MLP	ARIMA, MLP	ARIMA-MLP
Benmouiza and Cheknane (2015)	2015	ARIMA	NAR	ARIMA, NAR, ARIMA-TDNN, CARDS	ARIMA-NAR
Skopal (2015)	2015	ARIMA	MLP	ARIMA, MLP	ARIMA-MLP
Hirata et al. (2015)	2015	ARIMA	DBN, RBM and MLP	ARIMA, DBN	ARIMA-DBNN
Khandelwal et al. (2015)	2015	ARIMA	MLP	ARIMA, MLP, ARIMA-MLP	ARIMA-MLP based on DWT Decomposition
Shukur and Lee (2015)	2015	AR	MLP	AR-KF, ARIMA	AR-KF
Xie et al. (2015b)	2015	ARIMA, ARFIMA	ANN	Parallel hybrid models	Proposed nonlinear parallel hybrid models
Yu et al. (2014)	2014	SARIMA	NARNN	SARIMA, NARNN	SARIMA-NARNN
Mohammadi et al. (2014)	2014	ARIMA	MLP	ARIMA, MLP, GA–APSO based RBFNNs	GA–APSO based RBFNNs
Kumar and Thenmozhi (2014)	2014	ARIMA	MLP	ARIMA-SVM, ARIMA-RF, ARIMA, MLP, RF, ARIMA	ARIMA-SVM
Fard and Akbari-Zadeh (2014)	2014	ARIMA	MLP	ARIMA, MLP, AR, SVR	ARIMA-DWT-MLP
Xiao et al. (2014)	2014	ARIMA	MLP	ARIMA, MLP	ARIMA-MLP
Ruiz-Aguilar et al. (2014)	2014	SARIMA	MLP	SARIMA, MLP, parallel–series model	parallel–series model
Pati and Shukla (2014)	2014	ARIMA	MLP	ARIMA, MLP	ARIMA-MLP
Chaâbane (2014)	2014	ARFIMA	MLP	MLP, ARFIMA, ARIMA-MLP	ARFIMA-MLP
Jeong et al. (2014)	2014	SARIMA	MLP	SARIMA	SARIMA-MLP
Ren et al. (2013)	2013	ARIMA	MLP	ARIMA	ARIMA-MLP
Riahi et al. (2013)	2013	ARIMA	MLP	ARIMA	ARIMA-MLP
McDonald et al. (2013)	2013	ARIMA	SOFNN	ARIMA, SOFNN	ARIMA-SOFNN
Wang et al. (2013b)	2013	ARIMA	MLP	ARIMA, MLP, multiplicative hybrid model	Multiplicative hybrid model
Ye et al. (2013)	2013	ARIMA	DENFIS	ARIMA, DENFIS	ARIMA-DENFIS
Eswaran and Logeswaran (2012b)	2012	ARIMA	MLP	LR ESM, MLP, ARIMA	ARIMA-MLP
Hakan Aladag et al. (2012)	2012	ARFIMA	MLP	MLP, ARIMA	ARIMA-MLP
Eswaran and Logeswaran (2012)	2012	ARIMAX	ANFIS	ARIMA, ANFIS	ARIMA-ANFIS
Shi et al. (2012a)	2012	ARIMA	MLP	MLP, ARIMA, SVM	Hybrid models are viable alternatives, but they do not always produce superior forecasting performance for all time horizons.
Shi et al. (2012b)	2012	ARMA	MLP	ARMA, ARMA-MLP-Markov, ARMA-MLP	ARMA-MLP-Markov
Khashei et al. (2012a)	2012	SARIMA	MLP	SARIMA, FSARIMA, Watada's model	SARIMA-MLP
Wang and Meng (2012)	2012	ARIMA	MLP	ARIMA, MLP	ARIMA-MLP

(*continued on next page*)

4.3. Summary of series reviewed models

Development in series hybrid models since the first work proposed by Zhang (2003) leads to propose so many series models for time series forecasting in wide variety of areas. Distribution of these papers regarding to different types of series models and the modeling sequence is illustrated in Fig. 7. The most highlighted points of series hybrid models are given below:

✔ The most common sequence order in modeling linear and nonlinear parts of a time series is linear-nonlinear, which have been used by more than 90% of reviewed models. Moreover, among

Table 10 (*continued*).

Article	Year	Type of ARIMA model	Type of ANN model	Compared with	Superior model(s)
Khashei et al. (2012b)	2012	ARIMA	PNN	ARIMA, MLP, ARIMA-MLP	ARIMA-PNN
Xiao et al. (2012)	2012	ARIMA	ELNN	ARIMA, ELNN	ARIMA-ELNN
Shafie-khah et al. (2011)	2011	ARIMA	RBFNN	ARIMA, wavelet-ARIMA, FNN, MI + CNEA	Wavelet-ARIMA-RBFN
Wu and Chan (2011)	2011	ARIMA	TDNN	ARIMA, TDNN	ARIMA-TDNN
Chen (2011)	2011	ARIMA	MLP	ESM, ESM-MLP, ES-SVR, ARIMA, ARIMA-MLP, ARIMA-SVR	Hybrid SVR based models outperform ANN based models
Khashei and Bijari (2011)	2011	ARIMA	MLP	ARIMA, MLP, parallel–series architecture (3 models)	parallel–series model
Nourani et al. (2011)	2011	SARIMA	MLP	SARIMA, MLP, WANN, ANFIS, WANFIS	WANFIS
mer Faruk (2010)	2010	ARIMA	MLP	ARIMA, MLP	ARIMA-MLP
Khashei and Bijari (2011)	2010	ARIMA	MLP	ARIMA, MLP, parallel–series architecture (1 model)	parallel–series model
Mohamed and Ahmad (2010)	2010	SARIMA	MLP	SARIMA, MLP	SARIMA-MLP
Areekul (2010)	2010	ARIMA	MLP	ARIMA, MLP	ARIMA-MLP
Cadenas and Rivera (2010)	2010	ARIMA	MLP	ARIMA, MLP	ARIMA-MLP
Koutroumanidis et al. (2009)	2009	ARIMA	MLP	ARIMA, MLP	ARIMA-MLP
Aladag et al. (2009)	2009	ARIMA	ERNN	MLP, ARIMA-MLP, SETAR, ARIMA-ERNN	ARIMA-ERNN
Yu and Zhang (2008)	2008	ARIMA	ELNN	AR, ELNN	ARIMA-ELNN
Dıáz-Robles et al. (2008)	2008	ARIMAX	MLP	Deterministic MLR, ARIMAX, MLP	ARIMAX-MLP
Mohamed and Ahmad (2008)	2008	SARIMA	MLP	MLP, SARIMA	SARIMA-MLP
Valenzuela et al. (2008)	2008	ARIMA	MLP	AR, Cascade correlation ANN, MLP, GA, and fuzzy system, ANFIS and fuzzy system, RBFNN	Fuzzy-ARIMA-MLP
Shahwan and Odening (2007)	2007	SARIMA	ELNN	ARIMA, ELNN	ARIMA-ELNN
Mishra et al. (2007)	2007	ARIMA	ANN	DMSNN, ARIMA, RMSNN,	ARIMA-ANN
Aslanargun et al. (2007)	2007	ARIMA	MLP, RBFNN	ARIMA, Linear ANN, MLP, RBFNN	MLP-RBFNN
Aburto and Weber (2007)	2007	SARIMA	MLP	Naıve, Seasonal Naıve, SARIMA, MLP	SARIMA-MLP
Qu et al. (2006)	2006	ARIMA	RBFNN	ARIMA, RBFNN	ARIMA-RBFNN
Joy and Jones (2005)	2005	ARIMA	MLP	ARIMA	ARIMA-MLP
Lu et al. (2004)	2004	ARIMA	MLP	ARIMA, MLP	ARIMA-MLP
Zhang (2003)	2003	ARIMA	MLP	ARIMA, MLP	ARIMA-MLP

Table 11
Summary of reviewed papers using ARIMA-SVM series models.

Reference	Year	Type of ARIMA model	Type of SVM model	Compared with	Superior model(s)
Gurnani et al. (2017)	2017	ARIMA	SVM	ARIMA-ARNN, ARIMA-XGBoost, ARIMA-SVM, STL	STL Decomposition is more robust than Hybrid technique
Yuan et al. (2017)	2017	ARFIMA	LSSVM	ARFIMA, LSSVM, ARFIMA-MLP	ARFIMA-LSSVM
Rathod et al. (2017)	2017	ARIMA	NLSVR	ARIMA, NLSVR, TDNN, ARIMA-TDNN	ARIMA-NLSVR
Wang et al. (2017b)	2017	ARIMA	SVM	ARIMA, SVM	ARIMA-SVM
Karthika et al. (2017)	2017	ARIMA	SVM	ARIMA, SVM	ARIMA-SVM
Kavousi-Fard (2017)	2017	ARIMA	SVR-MCSO	ARIMA, ANN, SVR, SVR-GA, SVR-MCSO	ARIMA- SVR-MCSO
Oliveira and Ludermir (2014)	2014	ARIMA	SVR	SVR, ARIMA-SVR and PSO-SVR	PSO-ARIMA-SVR
Xie et al. (2015b)	2015	ARIMA, ARFIMA	SVM	Parallel hybrid model	Proposed nonlinear parallel hybrid model
Ming et al. (2014)	2014	ARIMA	SVM	ARIMA, SVM	ARIMA-SVM
Xie et al. (2013)	2013	SARIMA	LSSVR	ARIMA, SARIMA, CD, MLP, SVR, LSSVR, CD–LSSVR, SD–LSSVR	Proposed hybrid approach
Zhu and Wei (2013)	2013	ARIMA	LLSVM	ARIMA, SVM, ANN, parallel–series model	parallel–series model
Yan and Chowdhury (2013)	2013	ARIMAX	LSSVM	LSSVM	ARIMAX-LSSVM
Kavousi-Fard and Kavousi-Fard (2013)	2013	ARIMA	SMACSA-SVR	ARIMA, ANN, SVR, SVR-PSO	ARIMA-SMACSA SVR
Bouzerdoum et al. (2013)	2013	SARIM‘A	SVM	SARIMA, SVM	SARIMA-SVM
Sujjaviriyasup (2013)	2013	ARIMA	SVM	ARIMA, HWM, SVM	ARIMA-SVM
Nie et al. (2012)	2012	ARIMA	SVM	ARIMA, SVM	ARIMA-SVM
Shi et al. (2012a)	2012	ARIMA	SVM	ARIMA, SVM, ANN	Hybrid models do not always produce superior forecasting performance.
Zhang et al. (2012b)	2012	ARIMA	LSSVM	ARIMA-LSSVM, ARIMA-PLSSVM, ARIMA, PLSSVM, ANN, ANN-ARIMA	WT-ARIMA-PLSSVM
Zhang et al. (2012a)	2012	ARIMA	LSSVM	LSSVM, ARIMA, ANN	The proposed univariate LSSVM model
Guo et al. (2011)	2011	SARIMA	LSSVM	ARIMA, SARIMA, ARIMA-SVM, GM(1,1)	SARIMA-LSSVM
Zhang et al. (2008)	2008	ARIMA	SVM	MLP, ARIMA, SVM	ARIMA-SVM
Pai and Lin (2005)	2005	ARIMA	SVM	ARIMA, SVM	ARIMA-SVM

them the ARIMA-ANN models, especially ARIMA-MLP models are the most popular and widely used approaches.

✔ There are a few studies fall in to both linear–nonlinear and nonlinear–linear sequence modeling and make comparative studies about the accuracy of these two forms of models. The most important point that can be extracted from studies comparing two sequence orders is that since many researchers focus on using the linear-nonlinear series models, there are some evidences that the nonlinear–linear series models can obtain better performance (Khashei and Hajirahimi, 2018).

✔ Based on the existing comparisons in the literature, more accurate forecasting performance in sequential hybridization can be usually obtained when more powerful individual models are chosen as preliminary components.

Table 12
Summary of reviewed papers using ARIMA based series models.

Reference	Year	Type of ARIMA model	Type of nonlinear model	Compared with	Superior model(s)
Moeeni and Bonakdari (2017b)	2017	SARIMA	GEP	SARIMA-ANN, GEP, ANN	SARIMA-GEP
Mitra and Paul (2017)	2017	ARIMA	GARCH	ARIMA, GARCH, ARIMA-ANN	Hybrids models
Ch. Xu et al. (2016)	2016	ARIMA	GP	ARIMA	ARIMA-GP
Kane and Yusof (2013)	2013	ARFIMA	GARCH	ARFIMA	ARFIMA-GARCH
Barbulescu and Bautu (2012)	2012	ARIMA	GEP	ARIMA, GEP	ARIMA-GEP
Lee and Tong (2011)	2011	ARIMA	GP	ARIMA, GP, ANN, ARIMA-ANN, ARIMA-SVM	ARIMA-GP
Pwasong and Sathasivam (2017)	2017	QR	ERNN	ERNN, QRM	QR-ELNN
Khairalla et al. (2017)	2017	EXP	MLP	Parallel hybrid model	Proposed linear hybrid model
Khairalla et al. (2018)	2018	EX	MLP	ARIMA-MLP, ARIMA, MLP, EX, parallel hybrid model	Parallel hybrid model
Pwasong and Sathasivam (2016)	2016	QRM	CFBNN	ARIMA-RNN, CFBNN, LRNN	QRM-CFBNN
Adhikari and Agrawal (2014)	2014	RW	MLP and ELNN	RW, MLP, ELNN	RW-(MLP+EANN)
Zhang et al. (2013b)	2013	PCR	MLP	PCR, ANN	PCR-ANN
Eswaran and Logeswaran (2012a)	2012	LR	MLP	LR, MLP, ARIMA	LR-MLP
Maia and de Carvalho (2011)	2011	HESM	MLP	MLP, HESM	HESM-MLP
Chen (2011)	2011	ESM	MLP	ESM, ESM-MLP, ESM-SVR, ARIMA, ARIMA-MLP, ARIMA-SVR	ESM-SVR

Table 13
Summary of reviewed papers using ANN based series models. (Continue)

Reference	Year	Type of linear model	Type of neural network	Compared with	Superior model(s)
Al-Alawi et al. (2008)	2008	PCR	MLP	PCR, MLP	PCR-MLP
Bo et al. (2007)	2007	ARCH	MLP	ARIMA-ANN	ARCH-MLP
Yu et al. (2005)	2005	GLAR	MLP	Parallel hybrid models, ANN, GLAR	Proposed parallel hybrid model

Table 14
Summary of reviewed papers using SVM based series models.

Reference	Year	Type of SVM model	Type linear model	Compared with	Superior model(s)
Xiong et al. (2017)	2017	MSVR	Holt	ARIMA-ANN, Holt-ANN, MSVR, MLP, Holt	Holt-MSVR
Xiong et al. (2015)	2015	MSVR	VECM	VECM, SSVR, MSVR, ARIMA-MSVR, ARIMA-ANN	VECM-MSVR
Tang et al. (2013)	2013	SVM	DESM	ARIMA, DESM	DESM-SVM
Huang and Wu (2006)	2006	SVM	Unscented KF	Unscented KF, SVM, Unscented KF-ANN	Unscented KF-SVM

✔ According to the theoretical documents illustrated in the literature, the series hybrid models can at least improve the forecasting performance of the first based model employed in their structure.

4.4. Parallel–series hybrid structure

Another argument developed in the literature is related to propose a superior structure by combining parallel and series structures, which can improve the performance of both series and parallel hybrid models. Although, it can be inferred from parallel and series hybrid models, discussed in previous sections that these hybrid methodologies can improve the performance of individual models, there is no universal agreement on which hybrid structure should be used for achieving the most desirable performance. As mentioned, limited discussions and conclusions are only raised about this matter in few studies (Khairalla et al., 2017; McDonald et al., 2014; Khashei and Hajirahimi, 2017; Safari and Davallou, 2018; Yu et al., 2005; Xie et al., 2015b). This third hybrid structure is developed for the first time by Khashei and Bijari (2010). In this section, related articles are briefly reviewed based on three architectures presented for this structure.

Ruiz-Aguilar et al. (2014) have proposed three architectures of parallel–series hybrid models, employing SARIMA and ANN models. In this study, three different kinds of parallel–series hybrid models as well as SARIMA-ANN series hybrid model, and also traditional models are used. Experimental results show that the architecture-3 is a superior model in term of forecasting accuracy. Zhu and Wei (2013) have presented the first and second architectures of parallel–series models to exploit specific advantages of ARIMA and LSSVM models. Empirical results indicate that the architecture-1 can obtain better performance than architecture-2, series ARIMA-LSSVM hybrid model, and also single models such as ARIMA, ANN and LSSVM.

Wongsathan and Seedadan (2016) have implemented the architecture-3 of parallel–series hybrid models to improve the performance of both ARIMA and ANN models. Experimental results demonstrate that the hybrid model outperforms both components. Jeong et al. (2014) have proposed the parallel–series model, employing architecture-3 and using SARIMA and ANN models. Obtained results of this study confirmed that the parallel–series model can achieve superior forecasting performance than traditional SARIMA model.

4.5. Summary of parallel–series reviewed models

✔ Despite the successful application of various series and parallel hybrid structures presented in previous sections, the comparative studies demonstrate that there is no deterministic consensus for choosing the superior hybrid structure in order to access better forecasting performance.

✔ Recently, some researchers have started to discuss the need of the third hybrid structure to overcome limitations of series and parallel hybrid structures and simultaneously use unique advantages of both structures in order to obtain more accurate results.

✔ The reviewed papers clarify that the parallel–series hybrid structure can achieve more accurate results than series models (Khashei and Bijari, 2010, 2011; Ruiz-Aguilar et al., 2014; Zhu and Wei, 2013).

✔ Experimental results indicate that the architecture-3 can yield better performance in comparison with two other architectures of parallel–series hybrid structure (Ruiz-Aguilar et al., 2014; Zhu and Wei, 2013).

Table 15
Summary of reviewed papers using nonlinear-linear series models.

Reference	Year	Type of nonlinear model	Type of linear model	Compared with	Superior model(s)
Khashei and Hajirahimi (2018)	2018	MLP	ARIMA	ARIMA, MLP, ARIMA-MLP	MLP-ARIMA
Khashei and Hajirahimi (2017)	2017	MLP	ARIMA	Parallel hybrid models	Series models
Hajirahimi and Khashei (2016)	2016	ANN	ARIMA	ARIMA, ANN	Both ARIMA-ANN and ANN-ARIMA models
Wang et al. (2015)	2015	ELM	SARIMA	ARIMA, SARIMA, MLP, ELM	ELM-SARIMA
Alwee et al. (2013)	2013	SVR	ARIMA	ARIMA, PSOARIMA, PSOSVR, PSOSVR-ARIMA, PSOSVR-PSOARIMA	PSOSVR-PSOARIMA
Pham et al. (2010)	2010	NARX	ARMA	NARX, ARMA	NARX–ARMA
Che and Wang (2010)	2010	SVR	ARIMA	ANN, ANN-ARIMA, SVR, ARIMA, ARIMA-SVR	SVR-ARIMA
Purwanto et al. (2010)	2010	MLP	ARIMA	ARIMA-MLP, ARIMA, MLP	ARIMA-MLP
Xuemei et al. (2009)	2009	MLP	ARIMA	ARIMA	MLP
Sallehuddin et al. (2008)	2008	GRNN	ARIMA	ANN, ARIMA, ARIMA-ANN, MLR	GRNN-ARIMA
Zeng et al. (2008)	2008	MLP	ARIMA	ARIMA, MLP	MLP-ARIMA

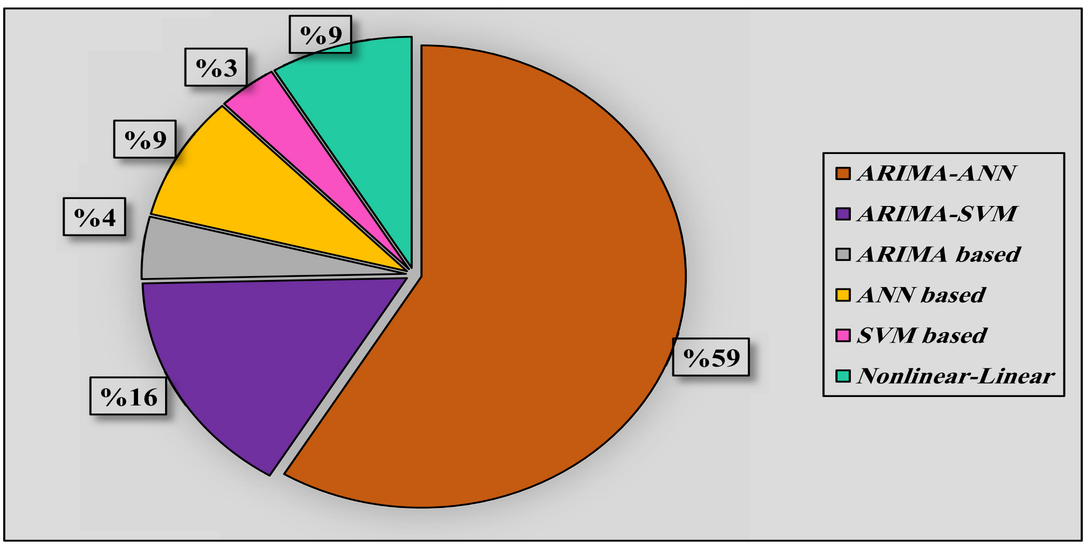

Fig. 7. Distribution of series hybrid models included in the review.

5. Some potential directions and trends for future researches

According to the literature of the component combination based hybrid models, i.e. series, parallel, and parallel–series, some potential directions and trends for future researches can be summarized as following points:

(A) Parallel Models

(AI) Developing mathematical exact methods for weighting
In the most of the existing parallel hybrid models, the weights of the components are usually obtained using meta heuristic algorithms. However, these methods can only yield local optimum weight of the forecasting models in an iterative time consuming procedure. A potential way to improve the performance of parallel hybrid models is to employ mathematical approaches that can directly achieve global optimum weights.

(AII) Developing supervised and/or unsupervised component selection procedures
The performance of the parallel hybrid models highly depends on the type of their components. Hence, the components should be carefully determined before constructing hybrid models. In order to further improve the performance of the parallel hybrid models in practical forecasting applications, it is crucial to develop the proper supervised and/or unsupervised algorithms for determining the type of components in the parallel hybridization.

(AIII) Developing theoretical and/or practical measures for choosing the number of components:
The number of components selecting in the structure of parallel hybrid models plays an essential role in the performance of hybrid model. For this purpose, the proper algorithms can be developed to determine the suitable number of components for parallel hybridization.

(B) Series Models

(BI) Applying weighting methods for series hybrid models:
Another future research work is to determine weights for each component in series hybridization. As it is mentioned before, the series models in the literature is commonly constructed based on the equivalent weight assumption for each constituent. However, the weights of each component may be different. Thus, the performance of series hybrid model can be improved by dedicating proper weight to each of the constructive components. Also, the series models can be developed for more than two components based on the specific characteristic of time series.

(BII) Developing numerical selection procedures for selecting the used components:
As similar fashion, the performance of series hybrid models is significantly depending on the type of their components. Thus the type of the constructive components should be determined before implementing series hybridization. Therefore, desired numerical algorithms should be developed for determining the type of components in the series hybrid structure.

(BIII) Developing theoretical and/or practical measures for choosing the number of components:
As similar fashion, based on the characteristic of the under study dataset, the researchers should determine the number of desired component of the series models by designing selecting algorithm.

(C) Series–parallel Models

(CI) selecting the proper architecture by combining series and parallel structures in different ways:
An essential phase in developing series–parallel hybrid structure is to select the proper combination of series and parallel hybrid structures among different alternatives. All series–parallel hybrid models proposed in the literature used the same combination of these two structures. So, the other possible combination choices can be developed for constructing series–parallel hybrid models in the futures.

(CII) Applying weighting methods
Another future research work is to determine weights for each component and/or structure in series-parallel hybridization. As it is mentioned before, the series models in the literature developed based on the equal weight assumption. Thus the components in this structure can be improved by adding weighting algorithms.

(CIII) Developing numerical selection procedures for selecting the used components:
As similar fashion, one alternative to improve the performance of parallel–series hybrid model is to determine the type and number of components.

6. Conclusion

Time series forecasting plays a substantial role in numerous fields of economic, engineering, medicine, management, finance, etc. it is the main reason of considerable developments, which are appeared in the literature of time series forecasting in order to provide accurate and reliable results. Although, there are a wide range of single models proposed for time series forecasting, they are not promising approaches can be applied on all situations with desired performance. In most papers, it is demonstrated that hybrid methods are appropriate alternative that can yield superior performance compared to individual options. Several hybrid models have been proposed in the literature of time series forecasting which can be generally categorized in three main categories based on the used structure. Hence, one of the most critical issues in hybridization is to choose the suitable structure in order to achieve the most accurate results. Several review papers have been written in the literature in order to classify of forecasting models based on the various criteria; however, in none of them has properly considered the structure of hybridization.

Following by this gap, in this study in the first step, three hybrid structures proposed in the literature of time series forecasting including: parallel, series and parallel–series structures are briefly described. Then, a comprehensive review is studied on developed papers in each category, totally more than 150 papers in time series forecasting. At last, detailed findings, remarks, and conclusions are presented regarding to specific characteristics of each hybrid structure. Maybe the most important and the most crucial points that can be extracted from reviewing the provided information in these papers can be summarized as follows:

- ✔ The performance level of the parallel hybrid models depends on the two major factors: combination function and weighting approach. In the linear combination function, the prediction accuracy is significantly affected by choosing the proper weighting method. Among static weighting methods, averaging and min error are the most popular approaches in reviewed papers. While, it is clearly pointed out that dynamic weighting systems can produce more accurate results in comparison with statics ones. Another extracted conclusion is that while linear combination function is a common strategy for constructing parallel hybrid models, employing nonlinear combination functions can lead to better performance.
- ✔ In series hybrid models, modeling sequence has a determinative role in the forecasting performance. The linear-nonlinear sequence especially ARIMA-ANN is the most common sequential modeling procedure proposed for constructing series hybrid models. While, in the comparative studies presented in the literature, it is documented that using nonlinear-linear sequence can result to better performance.
- ✔ The important point extracted from series and parallel structures is that there is no universal consensus about the parallel and series hybrid structures as a dominate hybrid strategy. Thus, selecting one of these structures is yet often the most challenging problem in hybridization area. In recent years, a few studies have been developed an integrated version of parallel and series hybrid methodologies in order to address this problem. Limited presented papers in this field verify the superiority of the parallel–series combination structure for time series forecasting.

The comparative analyzing in this paper could help the researchers in time series forecasting fields in order to select the proper hybrid structure and yield desired forecasting accuracy. Besides, some research gaps as well as theoretical and practical guideline provided for each hybrid structure suggested in this paper can help forecasting professionals for their future works.

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