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ABSTRACT

In the era of modern technology, the competitive paradigm among organisations is changing at an unprecedented rate. New success measures are applied to the organisation's supply chain performance to outperform the competition. However, this lead can only be obtained and sustained if the organisation has an effective and efficient supply chain and an appropriate forecasting technique. Thus, this study presents the demand-forecasting model, i.e., a good fit for the pharmaceutical sector, and shows promising results. Through this study, it is observed that combining forecasting algorithms can result in greater forecasting accuracies. Therefore, a combined forecasting technique ARIMA-HW hybrid[1] i.e. (ARHOW) combines the Autoregressive Integrated Moving Average and Holt' s-Winter model. The empirical findings confirm that ARHOW performs better than widely used forecasting techniques ARIMA, Holts Winter, ETS and Theta. The results of the study indicate that pharmaceutical companies can adopt this model for improved demand forecasting.

Introduction

In the pharmaceutical industry, demand forecasting is essential for optimising and managing complex business processes (MERKURYEVA and ALEXANDER SMIRNOV 2019). Transparent and unobstructed information flow directly affects supply chain (SC) dynamics (BOONE et al. 2019; FILDES, GOODWIN, and ÖNKAL 2019). Data sharing between the purchaser and seller in the SC network has been considered useful in avoiding the purported bullwhip impact and enhancing SC operations (BOYCE, JOHN, and KENT 2016). 'Recent technological developments enable designing useful forecasting models to increase supply chain management (SCM) efficiency (Habibeh Zeraati, 2019; IM, RAI, and LAMBERT 2019)'. Indeed, collecting data from several actors, such as the distributors, the healthcare providers and the customers (i.e. patients) becomes easier (SECGINLI, ERDOGAN, and MONSEN 2014). Digitisation brings companies to shift a flexible cost base, reduces the risk, and aligns the SC network with its demand forecasts (SCHNIEDERJANS, CURADO, and KHALAJHEDAYATI 2020; ZHANG and ZHANG 2018). Data collection through external and internal collaborations that include Vendor-managed Inventory (VMI), Electronic Data Interchange (EDI), and sales operations are more accurate and drive better

forecasting results (NASIRI et al. 2020; AGOSTINO et al. 2020). However, it should be pointed out that available technologies should be appropriately explored for computing demand forecasts to increase SC efficiency (PWC 2016). WELLER and CRONE (2012) stated that data are mostly collected for demand forecasting purposes by employing a collaborative information-sharing mechanism. From other sources like sales and operations, collaborative planning forecasting and replenishment and vendor managing inventory data help the manufacturers forecast accurately. According to Munim and Schramm (2017), the hybrid forecasting model ARIMARCH combining the Auto-Regressive Integrated Moving Average (ARIMA) and Autoregressive Conditional Heteroscedasticity (Walters and Archer) model enhances the forecasting accuracy when compared to that yield by the appliance of a single forecasting model.

Moreover, the Mean Absolute Percentage Error (MAPE) obtained by employing the state-of-the-art model ARIMARCH developed by Munim and Schramm (2017) has shown significant forecasting results applying model ARIMA and ARCH independently for forecasting. A combined forecasting technique that considers historical and current demand data records has been used to forecast demand for the

Human Immunodeficiency Virus (HIV) diagnostics. In particular, linear extrapolation has been applied to the data of the WHO survey for demand forecasting. In contrast, the Clinton Health Access Initiative (CHAI) has been used when dealing with the historical demand of countries that fall under CHAI's umbrella (WHO 2016). Based on the consolidated forecasting: 80% is accounted for from CHAI, and 20% are linear extrapolation. Deep learning tools can help achieve higher forecast accuracy by creating patterns in decision making rather than using a single model to forecast demand (THOMSON et al. 2019). By combining various machine-learning models; it will help to resolve issues of warehouse forecasting. Hence, the devised method's forecast error is less than 5% compared to predicting through a single model for forecasting methods; thus, the combined variants reveals better performance (ISLEK, S. G. O 2017).

Moreover, the stacked generalisation method developed for the decision support system reduces the error rate by 9% compared to forecasting through traditional processes like forecasting by using a model. NIKOLOPOULOS et al. (2016) worked on pharmaceuticals brands and generics to forecast the demand. For this instance, seven different forecasting techniques have been applied as deep learning tools to analyse the past 21 years' data set. The empirical result exhibits that both ARIMA and Holts Winter combined produces a more accurate forecast in a shorter period. In contrast, the Naïve technique has a more significant forecasting result for a period of 2 to 5 years.

Literature Review

Practitioners usually face significant challenges in understanding and applying forecasts due to the lack of available related literature review. Significant savings, improved communication, better working practices, and enhance forecast accuracy can be achieved by employing a sound decision support system for forecasting purposes (FILDES and GOODWIN 2020; DURAND 2003). For this instance, Enterprise Resource Planning System (ERP) is used to get accurate real-time information and forecast computed results by applying the available models in the ERP systems (JanePHILLIPS and NIKOLOPOULOS 2019). The following systems have been studied thoroughly, the available functionality in the ERP system for demand forecasting. Table 1 indicates seven ERP systems that are mostly used for this purpose.

Demand Forecasting and Integrating Systems

Furthermore, by deploying an ERP system and using demand forecasting functionality appropriately with accurate data, an organisation would reduce inventory levels (TIWARI 2020; ERKAYMAN 2018). Higher inventory levels are a significant risk in the SC because it freezes the capital and holds inventory cost that leads a company towards bankruptcy (CRONE and D. S 2013). On the other hand, integrated systems with suitable models enable manufacturers to decrease the gap between actual and forecast demand; thus results in competitive advantage (HININGS, GEGENHUBER, and GREENWOOD 2018; AYTAC and WU 2017). Moreover, users' involvement in the forecasting model's development may increase the model's probability of success. On the one hand, the integrated system allows seamless information synchronisation between departments resulting in better estimations. On the other hand, information sharing among multiple SC players reduce uncertainty about the requirements, resource allocation and their availability.

Demand Forecasting and Healthcare Supply Chain

The concept of mass production is not only applicable to the fast consumer goods manufacturing companies but also the pharmaceutical industry because demand estimates are retrieved from the patient's consumption (FILDES and GOODWIN 2020; SALAM and KHAN 2018). For instance, inappropriate demand calculation against patient data and fighting against deadly pandemics lead to loss of lives; an increase in demand due to an increase in population makes the pharmaceutical industries' scope more critical and complex (REES 2011). The pharmaceutical industry's production network offers associations to build up their plan for dealing with the open doors and dangers to the pharmaceutical inventory network (Whewell, 2016). Improvement of the ideal framework can significantly impact demand forecasting, which is the tool to gauge SCM and its optimisation (PAPAGEORGIOU 2009). Most business procedures direct that a level of independence is required at every assembling and appropriation site (RUSCA et al. 2020; FORDYCE 2009). However, weights to coordinate reactions to worldwide requests while minimising cost suggest that concurrent arrangement of generation and dissemination crosswise over plants and distribution centres should be embraced (TOMASGARD, E. H. 2005). Therefore, accurate forecasting of the demand at both local and global levels is an essential driving factor to succeed (BOYCE, JOHN, and KENT 2016). To forecast demand for Antiretroviral medicines and HIV diagnostics in low and medium-income countries, CHAI has adopted consolidated demand forecasting methods to forecast the demand for drugs to cure HIV patients (WHO 2016).

Shortages of active pharmaceutical ingredients can result in life losses (GALARRAGA et al. 2007). Thereby, adequate demand forecasting of these life-saving drugs is mandatory as directed by global regulatory authorities. According to WALTERS and ARCHER (2006), customer loyalty is lost when the organisation loses

Table 1. ERP systems to forecast demand.

No.	ERP SYSTEM	METHOD	MODEL	REFERENCE
1	SAP	Time Series	First Order Exponential Smoothing-FOES, Second Order Exponential Smoothing-SOES, Moving Average-MA, Dynamic Moving Average, Neural Networks, Regression Family (Linear, Dynamic, ARIMA, SARIMA)	(SAP 2017)
		Seasonal	Seasonal Trend-Model, Seasonal Trend-Model with Fixed Period Groupings, Intermittent Forecast-Model, Declining Demand Forecast-DDF	
		Causal	Intervention Models (Smoothing IMAX), Causal Dynamic Regression (ARX), ARIMAX and SARIMAX, Causal CI and Neural Networks	
		Judgemental Approach	Delphi, PERT, Expert Opinion, Market Surveys, Jury of Expert Opinion	
2	ORACLE and JD EDWARDS	Forecasting methods	Percent Over Last Year, Calculated Percent Over Last Year, Last Year to This Year, Moving Average, Linear Approximation, Least Squares Regression, Second Degree Approximation, Flexible Method, Weighted Moving Average, Linear Smoothing, Exponential Smoothing, Exponential Smoothing with Trend and Seasonality.	(ORACLE 2017)
3	MICROSOFT	Subjective / Qualitative Objective Quantitative Time Series Models	Delphi Method, Expert Opinion, Market Research	(Yurdal et al., 2017)
		Base Level, Trend Seasonality, Noise Causal Models	Smoothing Models Decomposition Models Dynamic Regression, ARIMA Model	
4	EPICOR	Forecasting methods	Weighted Average	(EPICOR 2017)
5	QAD	Sales Forecasting Technique Time Series	Trend, Seasonal, Horizontal, Cyclical Double Moving Average-DMA, Double Exponential Smoothing-DES, Linear Exponential-LE, Classic Decomposition-CD, Simple Regression-SR	(QAD 2016)
		Best Fit	Sum of the all-time series method	
6	INFOR and LAWSON	Forecasting methods	Moving average, Two-period weighted average, Exponential smoothing, Adaptive exponential smoothing	(INFOR 2017)
7	SAGE / FORECASTPRO	Forecasting methods	Expert Selection-ES, Exponential Smoothing-ES, Box-Jenkins, Dynamic regression-DR, Event-model, Multiple-level models-ML-M, New Product Forecasting, Seasonal Simplification -SS, Low Volume Models, Curve Fitting, Simple Methods	(Sage, 2013)

sight of market demand. In this vein, appropriate demand forecasting leads to create a relationship between suppliers and customers. SEKHRI (2006) explains that to maintain supply and demand globally; it is essential to have a better forecasting model that will increase the products' viability; hence, the better the forecast, the more the products are accessible. Nevertheless, computing demand accurately is a fundamental component of guaranteeing the adequate supply of life-saving drugs.

Forecasting Accuracy in Pharmaceutical Supply Chain

Pharmaceuticals face many challenges due to structural, technological, and regulatory problems, and collaboration among SC partners is challenging (FILDES and GOODWIN 2020). Accuracy in risk assessment cannot be analysed using a single point deterministic approach (KIELY 2004). However, stochastic strategies, for example, Monte-Carlo based analysis, which accumulates instability through probabilities, could be a better choice. According to PETERSEN (2004), it is essential to know that forecasting accuracy is worth gaining the support of top management. As the pharmaceutical industry becomes very volatile and rivals among companies increases to gain competitive advantage, it is essential to have an appropriate demand forecasting mechanism with maximum accuracy and low forecast error .

Impact of Information Sharing in Supply Chain

One of the most important factor that reduces supply chain complexity and inaccuracies is supply chain visibility, it has wider impact on supply chain performance; application of Internet of things will be an asset in this regard (AHMED et al. 2021). Furthermore, the sharing of information among suppliers and manufacturers increases the forecast accuracy that meets customer demand (GÉRARD and MARTIN 2001). An effective SC execution requires the producer to share their necessary information (DEY, A. N 2013). Li and Yu (2017) explains that sharing credible demand forecasts from both the manufacturer and supplier could positively impact. To cope with demand uncertainty and have more accurate forecasts, it is essential to have a bi-level decision framework (GUPTA and COSTAS 2000). The first level comprises the decisions where generation choices are made things that are in trend. While the second level involves production, where network choices are deferred in a 'keep a watch out' mode, i.e. advancement in the respective area or bent on the search for the changing trends.

According to REES (2011), pharmaceuticals supply chains dealing with complex situations, intelligent information, and communication systems must deal with this situation. Pharmaceuticals and other manufacturing companies break the geographical boundaries and expand their businesses outside their origin and move towards globalisation. RADHAKRISHNAN et al. (2011) explain that driving organisations towards sustainable integration could be exerted by establishing a formal system monitoring all partners' practices in the SC network. However, this process requires constant monitoring of the systems by both internal and external SC partners. STADTLER and KILGER (2005) suggest blended SCM procedures, frameworks, and associations will lead to reduced inventories, expanded limit usage, decreased request lead time, fewer stock-outs, and lower IT framework support costs.

Factors Effecting Supply Chain Efficiency

Additionally, PETERSEN (2004) highlights the pharmaceutical industry's integrated system's role through Collaborative Planning, Forecasting, and Replenishment (CPFR). CPFR helps the supplier plan ahead, which automatically reduces the lead time of active ingredient. In demand forecasting, there is not only internal factors like top management support, well-educated and experienced demand forecaster, and an updated integrated system (CANDAN, TASKIN, and YAZGAN 2014). Besides, external forces, i.e., seasonal and epidemic diseases, active ingredients rate, human factors, market shares of the competitive products, and marketing conditions, also play a significant role in biased forecasted accuracy (MERKURYEVA and ALEXANDER SMIRNOV 2019). Forecasting is considered one of the critical components To achieve SC competitiveness (DEY, A. N 2013). However, it becomes a complicated task to incorporate different parameters, such as uncertainty in demand for various products that make non-linearity in-demand functions. Advanced forecasting technique fuzzy artificial neural network is recommended by HASIN, GHOSH, and SHAREEF (2011) for best demand estimation in highly complex scenarios. Forecasting in an uncertain and complex environment requires a scenario analysis tool and to address the issues of this tool; an expert or team of experts that have appropriate knowledge of demand forecasting are needed to access the situation and act accordingly (HININGS, GEGENHUBER, and GREENWOOD 2018). PISHVAEE and FARIBORZ JOLAI (2008) suggested a method based upon the fuzzy theory set used to cope with uncertain parameters.

Challenges in Implementing Integrated Systems

The implementation of such an integrated system faces obstacles that are examined and categorised by JHARKHARIA and SHANKAR (2005) the researcher

suggests three-level categorisation. Top-level barriers include resistance to change according to systems requirement, low inventory network incorporation and disparity in trading partners. Mid-Level barriers have data security dangers, a dread of data framework breakdown, and fear of SC breakdown. Lack of IT awareness related to SC is at the last level (FORDYCE 2009). Furthermore, SAHAY and MOHAN (2003) explain that to obtain customer satisfaction, Indian pharmaceuticals and other industries aligned their business goals with SC goals, which subsequently resulted in an increased SC performance and better demand forecasting via integrated systems. In their research, 10% of the respondents who belong to the pharmaceutical industry rated demand-forecasting 4.22 out of 5.

By reviewing the literature, a gap has been identified under the stated subject, 'A *hybrid demand forecasting model for greater forecasting accuracy: The case of the pharmaceutical industry*'. There is little evidence that suggests incorporating demand forecasting mechanisms with information and communication technology systems. SCM and information technology are young but rapidly developing fields compared to Mathematics, Physics, Statistics, etc. (CANDAN, TASKIN, and YAZGAN 2014). The pharmaceutical industry has higher forecast errors due to external factors, i.e., regulatory, political, entry of new products with the same formulation, change in technology, doctors, and pharmacist attraction towards competitors' brand. The pharmaceuticals are encountering both the situational stock-outs and excessive inventory due to frequent forecasting errors.

Method and Forecasting Models

This section highlights the techniques and methods used to develop a combined forecasting model, as discussed in this paper. The combination is developed using two frequent, but separately used models, i.e. Autoregressive Integrated Moving Average (ARIMA) model and Holts Winter model. A combined model we propose in this paper will be referred to as the ARHOW model.

Data and Technique

For this quantitative research, we gained access to the actual sales data of six different drug classes from six pharmaceuticals in Pakistan. It is also worth noting that all six drugs have different formulations, which adds to this research's depth and breadth and justifies the model's versatility in any given scenario. It is meant to be the aggregation of both models, i.e. ARIMA and Holt's-winter forecasting model, which we name the ARHOW Model.

Autoregressive Integrated Moving Average Model (ARIMA)

CHASE, J (2013) describes the application of the ARIMA model. It is the forecasting technique that integrates vital components of time-series and methods of regression. In 1970, George Box and Gwilym Jenkins introduced the ARIMA forecasting method, and they developed a comprehensive approach for forecasting (JR. 2013).

ARIMA (p,d,q) models gather relevant factors from the historical data by using auto-correlation between them to distinguish those slacked request verifiable qualities that best anticipate future demand; whereas p is the order of Autoregressive (AR) term, q is the order of MA term

$$z_{t =\ \beta_\emptyset}\ +\ \emptyset_1 z_{t-1}\ +\ \emptyset_2 z_{t-2}\ +\ e_t\ +\ \theta_1 e_{t-1}\ +\ \theta_2\ e_{t-2}$$

(1)

Where: $z_{t/d}$= Forecast for t periods
  $\beta_\emptyset$ = Constant
  $\emptyset_p z_{t-p}$ = Linear combination Lags of z up to p lags
  $\theta_q e_{t-q}$ = Linear combination Lags of forecast errors up to q lags

ARIMA can demonstrate cycle and regularity, and is mainly used for mid-term aggregate forecasts and present far superior estimations than time series models or even casual models; explained by STADTLER and KILGER (2005) explicitly considers dependent demands. Additionally, different components, for example, informative factors that impact request. It is also considered a good fit for the Mean Absolute Percentage Errors (MAPE) calculation.

Furthermore, GUJARATI, PORTER, and GUNASEKAR (2012) states that the ARIMA model helps analyse the time series's probabilistic properties and develop single or multi-equation models. (MORITZ et al. 2015) explained that the fundamental thought for analysing a time series data is that there is a straightforward yet extensive arrangement of useful models that can speak to numerous conceivable examples of information found in time series. For a stationary time-series, we can envision the information creating process as a weighted blend of earlier perceptions in addition to an irregular request term. Besides, identifying the ARIMA model parameters (i.e. p, q and d) is often challenging. Thereby, we use R software's statistical package; it is widely used in the relevant literature (Bokde et al., 2016, DHAMO and PUKA 2010b). Moreover, 'R' generated the best combination of p, d and q values because it estimates the value of the parameter based on AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion).

Holt's-winters' method

In 1957, Charles C. Holt extended the single exponential smoothing to incorporate a so-called linear trend factor, to enable the forecasting model to consider the nature of demand patterns (CHASE, J 2013). The resulting model is the double exponential smoothing that integrates two smoothing constants α and β, whereby the first models the series level and the trends whereas, the second reflects the seasonality (GELPER, FRIED, and CROUX 2010). In 1960, Peter R. Winters developed Holt's strategy by including a seasonal component. The Holt's Winters' strategy, otherwise called the winters' technique, utilises three conditions to represent level, pattern, and seasonality. It is fundamentally the same as Holt's strategy; however, it expands the third condition to describe seasonal patterns (Ahmad, 2021; Laouafi, 2014). Additionally, these constants should be benchmarked from the [0,1] interval. The combined model is shown in equation 5.

$$L_t = \alpha(Y_t\ - S_{t-s})\ +\ (I-\alpha)(L_{t-1} +\ b_{t-1})$$ (2)

$$b_t =\ \beta(L_t\ - L_{t-1})\ +\ (I-\beta)b_{t-1}$$ (3)

$$S_t = \gamma(Y_t\ - L_t)\ +\ (I-\gamma)S_{t-s}$$ (4)

$$F =\ L_t +\ b_t m +\ S_{t-s+m}$$ (5)

Where: $L_{t/d=}$ Series level
  $b_t =$ =Shows trend
  $S_t =$ =Seasonal trend
  F = Forecast for m periods

Equations 2, 3 explains the level and the trend (L_t and b_t). The level equation shows a weighted average between the seasonally adjusted observation and the non-seasonal forecast. The trend equation shows a trend of the time series which is similar to Holt's linear method, whereas, equation 4 defines a weighted average between the current seasonal index and the past seasonal index, where m and Y_T represents several seasons, time series that are under observation, respectively. JR. (2013) defines the seasonal element is comparable to a seasonal index, a ratio of the data set's current values. The parameters α, β and γ can be optimised by minimising some statistical error metric such as the MAPE. Most demand forecasting solutions inevitably find the optimal α, β and γ for the time series under investigation. Another method used is a grid search method that calculates the final optimal parameter values. According to Jean-Marie Dufour (2019), grid search is a type of algorithm used for parameter optimisation. It could be set up by defining vectors consisting of lower bounds and upper bounds between the space of nuisance parameters. Furthermore, forecasting through the Holts-Winter method and finding values of the parameters α, β and γ forecast package of statistical tool 'R' has been used (Hyndman and Khandakar, 2008).

ARHOW Model

This study aims to construct a model that enhances the forecasting accuracy, for this combination of two statistical models has been tested whether it is working appropriately or not. Consolidating estimates is conceivable just if there is more than one sensible source of estimations. In this case, first historical data will be forecasted through the ARIMA model, and errors will be calculated. Later it will be forecasted through Holt's Winter forecasting method, errors will be calculated, and the results obtained from both forecasting methods will be tailored in the model equation (6) mentioned below. Higher volatility or inaccuracy in forecasting warrants the utilisation of consolidated or combined forecasting model (THOMSON et al. 2019; ZHANG and ZHANG 2018). The manner of thinking around weighted consolidated forecasting, otherwise called composite forecasting, is not new (ISLEK, S. G. O 2017). The point has been contemplated for quite a long time, and experimental confirmation demonstrates that the blend of techniques tends to outflank most single estimation strategies. Whilst forecasting through an individual model like ARIMA and Holt's Winter, volatility and other external factors like seasonality may impact the results. ARIMA outperforms Holt's Winter if seasonality exists and combining model helps mitigate the data's volatility. MARKOVSKA, BUCHKOVSK A, and TASKOVSKI (2016) concluded in their comparative study that the ARIMA model gives more accurate results when the weekly and monthly time series is used. However, Holt's Winter model is more suitable for prediction when the daily time series is used.

CHASE, J (2013) explained by fitting together the results of independent forecasts of each model, the business forecaster endeavours to build up the ideal estimates. As a rule, the composite forecast of a few scientific and judgemental strategies has been demonstrated to beat the individual estimates of any strategy used to create the composite. Consolidating estimates is valuable only when one is indeterminate as to which technique to apply or when the current strategy alone does not give a sufficient measure of precision. Regardless of the possibility that one method can be recognised as best, joining might be valuable if

alternate strategies contribute to greater forecast accuracy (MARKOVSKA, BUCHKOVSK A, and TASKOVSKI 2016). Following is the model equation for obtaining a consolidated forecast.

$$ARHOW = \beta_{\circ} * ArimaForecast + \beta_1 \\ * Holt'sWinterForecast \qquad 3.4.$$

Where ARHOW = Combined Weighted Forecast
$\beta_{\circ}$ = Weight of ARIMA Forecast
β_1 = Weight of Holt's Winter Forecast

ARIMA Forecast and Holt's Winter obtained by applying models over the training set.

For this research, actual sales data have been collected from the selected pharmaceuticals from Quintiles (formerly known as the IMS-health) database (Table 2).

Data collected from the source includes injections, tablets, capsules and suspension of different potencies are used for analysis perspective almost six brands of each therapeutic class has been selected. Analysis over one therapeutic class has shown here in Table 3, and rest are shown in appendix section with reference (Remaining results of forecasts of Table 3). The following steps were carried out for systematic statistical procedures or modelling. For computation purposes, the above therapeutic classes and brands' sales data have been extracted from 2012 to 2016. The second step transforming the complete data set in training and test data set. Therefore, 74% of the total observation is considered as a training set that is (58×0.74 =43), and remaining observation is taken as a test set that is (58×0.26 =15), i.e. 43 months of sales data considered as training data set and 15 months of sales data considered as test data set. A comparison of test data against forecasted value has been used to measure forecast accuracy.

Empirical analysis and findings

Demand forecasting via ARIMA model

In this section, steps involved in forecasting through the ARIMA model will be discussed, and interpretation of the results obtained will be in focus. The following are the steps involved in forecasting through the ARIMA model. While forecasting through ARIMA CHASE, J (2013) explained, it should be stationary on mean and variance. Stationarity can be achieved by

Table 2. Companies, formulation, potency, and brands selected for the research.

Company Name/ Product	Ceftriaxone IV (Inj. 1 gm)	Clarithromycin (Tab. 250 mg)	Ciprofloxacin (Tab.250 mg)	Cefixime (Cap. 400 mg)	Omeprazole (Sus. 20 mg)	Montelukast (Tab. 10 mg)
GETZ	Getofin	Claritek	Novidate	Cefiget	Risek	Montiget
SAMI	Oxidil	Rithmo	Ciplinz	Caricef	Teph	Montika
BOSCH	Cefxone	Maclacin	Inoquin	Cebosch	Omezol	Beasy
BARRETT HODGSON	Inocef	Megaklar	Ciproquine	Cefspan	Losec	Aerokast
MACTER	Titan	Ultima	Cycin	Maxima	Sante	Mntk
HIGH-Q	Hizone	Pylocar	-	-	Ruling	Freehale

taking the difference of original data or by log transformation. Thus, by making it a stationary trend and seasonality removes from data. So as in the case, first-order differencing removes trend, and log transformation tend to remove seasonality. The rest has done by 'auto.arima' command in 'R'. ARIMA forecasting through the 'R' package automatically fit the best model over the data set based on best AIC (Akaike Information Criteria) and BIC (Bayesian Information Criteria) value (Hyndman et al., 2020). Therefore, there is no need to reinvent the wheel to fit the model and forecast manually.

Demand forecasting via holts winter model

The Holts Winter model has already been discussed earlier in the methodology section. In this section, steps involved in forecasting through the Holts Winter model will be discussed, and interpretation of the results obtained will be in focus. COGHLAN (2015) Holts Winter model is a parameter-based demand forecasting method, so it is necessary to assign weights to parameters, i.e., alpha, beta, and gamma. More weightage, i.e. near to 1, refers that the model considered most recent observations to assign more weights to forecast for a short term with accuracy. Forecast package in 'R' has built-in capabilities if the forecast for short-term period or forecasting less than that of training set package automatically assigns more weights to recent observations. The computation has been done through 'R' by running the command 'forecast.holtwinters' explained and applied by DHAL and RAO (2014) and ALBALAWI and ALANZI (2015) in their papers.

Demand forecasting via combine forecast/ARHOW model

Thirty-four brands of pharmaceutical sales data that belongs to 6 therapeutic class are tested and analysed. To get a complete insight of model functioning,

a famous brand (Getofin) of 'Ceftriaxone', a therapeutic class often used to cure middle ear infections, meningitis, pneumonia, urinary tract infection, and other acute diseases are chosen. The method of combining the different models are not new researchers applied this technique in their researches with slightly different/unique approaches by tweaking the combining techniques like (CAIADO 2010), (WEI and YANG 2012), (CHAN and PAUWELS 2018), (MUNIM and SCHRAMM 2020) and others applied it in many disciplines. In this paper, the combine-forecasting technique has been applied in a slightly different manner. Figure 1 indicates a step-by-step procedure to test the efficiency of the model:

Results

To further test the efficiency and validity of the ARHOW model, the results of two more models; Exponential Time Series (ETS) and Theta are compared and illustrated in Table 3. By comparing the result of ARHOW forecast against ARIMA, Holts-Winter, ETS and Theta forecast, it is concluded that the ARHOW forecast is still significantly better concerning the models used in this study.

Table 3 shows the result obtained from the ARHOW model forecast of one therapeutic class brand, i.e. GETOFIN of 'Ceftriaxone IV (1 gm Injection)'. Moreover, the remaining therapeutic classes that comprise of 33 brands can be seen in the appendix section. Table 3 shows the results of the forecast through ARIMA, Holts Winter, ETS, Theta and ARHOW model, the value of forecasts is 12,259, 12,887, 12,631, 12,617 and 11,933, respectively, against actual sales units, i.e. **11,970,** which clearly explains there is the least deviation between ARHOW model's forecasted value and actual sales. Furthermore, the forecasted models' MAPE's are 5.64%, 9.37%, 6.33%, 6.21 and 1.99%, respectively, suggesting that the ARHOW demand predictions provide greater accuracy than other models.

Table 3. Forecast results of (therapeutic class) Ceftriaxone IV (1 gm injection) Getofin, remaining results are illustrated in the Appendix section.

| DATE	UNIT SALES	ARIMA	HOLT'S WINTER	ETS	Theta	ARHOW
01/08/2015	1,187	1,186	1,174	1,186	1,186	1,152
01/09/2015	1,166	1,169	1,147	1,168	1,168	1,140
01/10/2015	1,081	1,094	1,075	1,094	1,094	1,067
01/11/2015	906	939	935	941	941	908
01/12/2015	717	767	779	771	771	734
01/01/2016	589	648	671	653	652	612
01/02/2016	591	648	683	654	654	606
01/03/2016	666	716	763	724	723	665
01/04/2016	750	792	850	801	800	732
01/05/2016	779	819	879	827	826	756
01/06/2016	765	807	862	814	813	747
01/07/2016	733	779	813	785	784	732
01/08/2016	703	752	778	758	757	712
01/09/2016	679	731	749	736	734	695
01/10/2016	658	712	729	717	715	677
Total	11,970	12,559	12,887	12,631	12,617	11,933
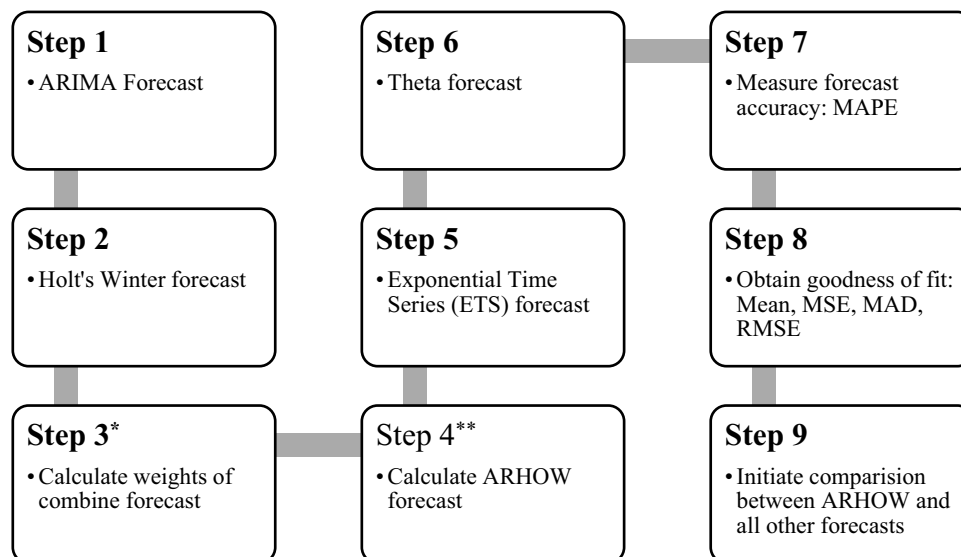
Figure 1. Step-by-step procedure to develop & test ARHOW model. * Compute weights i.e. β_0 and β_1 of combine forecast/ARHOW model. (There are various methods and techniques used to optimising weights for combine forecast but most common, preferred, reliable, easy to use, understand and interpret method is regression. For this test data set, therapeutic class is taken as the dependent variable. The forecast of the ARIMA model's forecast and the Holts Winter model is considered an independent variable).** Insert the results obtained from 1st, 2nd and 3rd steps in forecast equation (6) to get the ARHOW forecast against test data set.

Table 4. Descriptive Statistics (therapeutic class) Ceftriaxone IV (1 gm injection) Getofin.

GETOFIN	MEAN	MAD	MSE	RMSE	MAPE
Sales in Unit	798				
ARIMA Forecast	*837*	*39*	*1,883*	*43*	*5.64*
Holt's Winter Forecast	*859*	*66*	*5,414*	*74*	*9.37*
ETS Forecast	*842*	*44*	*2,376*	*49*	*6.33*
Theta Forecast	*841*	*43*	*2,285*	*48*	*6.21*
ARHOW Forecast	*796*	*16*	*334*	*18*	*1.99*
Naïve Forecast	*808*	*65*	*7,650*	*87*	*9*

Furthermore, Table 4 shows the descriptive statistics of the chosen therapeutic class and illustrates goodness of fit of forecasts obtained from ARIMA, Holts Winter, ETS, Theta, Naïve and ARHOW models. By analysing the deviation of the statistics (MAD, MSE, RMSE and MAPE); it can be easily comprehended that ARHOW model has the least deviation among all the models considered in this research. Furthermore, the Mean of ARHOW model is closely revolving around actual sales data of all the therapeutic classes. The forecast accuracy can be measured by comparing the Mean Absolute Percentage Errors of forecasts obtained from ARIMA, Holt's Winter, ETS, Theta, Naïve and ARHOW models (Table 4). Thus, results from (Tables 3 and 4) and all other therapeutic classes present in appendix section indicates that ARHOW model has greater forecasting accuracy.

Conclusion

In this study, we develop and introduce a new hybrid forecasting model, combining the ARIMA and the Holt's models. Based on data analysis and empirical findings, it is concluded that the ARHOW model outperforms both forecasting technique that is ARIMA and Holts Winter, which are widely practised for forecasting in industries across the globe. Forecast accuracy, i.e. the Mean Absolute Percentage Error, the goodness of fit test, i.e., the Mean, the Mean Absolute Deviation, the Mean Square Error and the Root Mean Square Error signifies the efficiency of the model and suggest implementing this technique for forecasting in the pharmaceutical industry. Results based on selected therapeutic class for research also indicate that the developed model fits for all the brands and is equally beneficial for all the pharmaceuticals. Moreover, the descriptive statistics of models ETS, Naïve and Theta used to compare against ARHOW model clearly depict that the ARHOW model is the most efficient among all the forecasting models and techniques. Furthermore, it also helps manufacturers to plan and replenishes stock/inventory based on their demands that prevent manufacturers from being trapped in neither bullwhip effect nor stock out situation.

Nevertheless, it also provides a basis for the forecasting system provider to tweak its forecasting model. It also provides a foundation to incorporate combined forecasting mechanisms in integrated systems as no integrated system provider combines forecasting functionality in their systems. Integrated system providers can develop an argument window by considering the time horizon, nature of data, formulation, brand, forecast period, and strength. Manual adjustments can allow the forecaster to tweak forecast parameters as per need. This empirical study exhibits significant outcomes; however, this research has certain limitations due to time and data constraints: Firstly, it only provides evidence of success in Pakistan's pharmaceutical

industry. Secondly, there are numerous therapeutic classes available, but only a few are considered in this research. Finally, there are many stock-keeping units (SKU's) available for specific brands of therapeutic class, but only a handful was considered in this research.

Thus, the developed model tested on the few therapeutic class of pharmaceutical industry other therapeutic class can be tested. Moreover, it can be tested in other industries like agriculture, textile, automotive, etc., which can surely increase the model's reliability. Furthermore, a combination of different models other than ARIMA and Holts Winter can be tested like Neural Networks with ARIMA or Holts Winter. Rather than employing two models, multiple models can be used over pharmaceutical or other industries. These findings could further be taken forward. There is still room for tweaking this model; utilising different methods to optimise the selected model parameters for combination other than the method used here.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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