Improving Forecast Accuracy with Hybrid Time Series Forecasting and Machine Learning Methods A Case Study of a Pharmaceutical Company

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Abstract

Pharmaceutical industry is instrumental to the well-being of people around the world as it deals with the discovery, development, production and marketing of drugs and medications, which are one of life's necessities. Recently, there is an emerging phenomenon that some hospitals in Vietnam must suppress their operation due to the deficiency of medical supply, and thus affecting patients who are in the need for treatment. One of the factors contributing to the situation is the incapability of providing these commodities on time from pharmaceutical companies, which results from their inaccurate forecasting. This paper investigates the application of machine learning algorithms in time series forecasting, specifically focusing on Support Vector Regression (SVR) to improve forecast accuracy. It evaluates the performance of two time series models, including ARIMA and Holt's Trend, and three types of SVR, including Linear kernel, Polynomial kernel, and Radial Basic Function (RBF). The evaluation is based on the Mean Absolute Percentage Error (MAPE) metric, which measures the accuracy of the forecasts. The study then proposes hybrid models that combine SVR with traditional time series models via ensemble methods and compares their performance with the individual models. Finally, a case study of a pharmaceutical company is performed to assess the impacts of these methods. The results demonstrate that the hybrid ensemble method achieves lower MAPE values compared to the individual models. These findings offer promising insights and highlight the potential of the proposed hybrid models in improving forecast accuracy.

Keywords
Forecast accuracy, time series methods, SVR, MAPE, ensemble.

1. Introduction
Medications, integral to enhancing lives, command significant attention and government investment within the pharmaceutical industry. Aided by data from the U.S Census Bureau Annual Survey of State and Local Government Finances, healthcare spending represents a substantial portion of state and local expenditures, ranking among the top sectors. In OECD countries, healthcare expenditure outpaced other sectors during the 1990s and early 2000s.

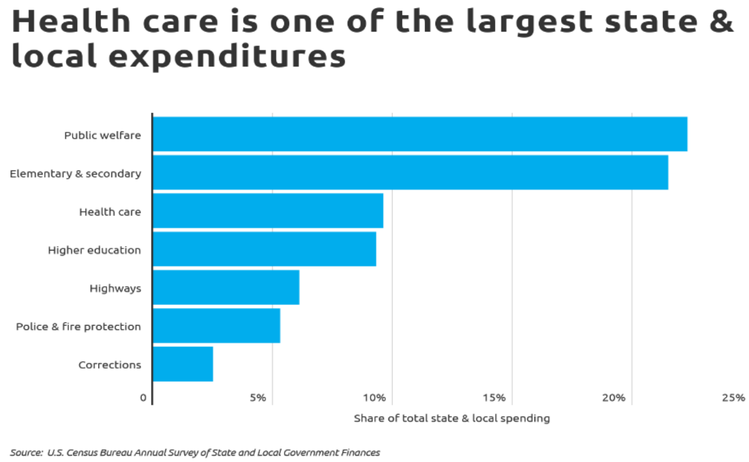

Figure 1. Huge expenditure on health care

Vietnam mirrors this trend with a growing commitment to healthcare reform, evident in increased national budget allocation. Yet, despite these efforts, a healthcare crisis persists, highlighted by shortages of essential medications and medical equipment in major Vietnamese hospitals. Ministry of Health data reveals that a majority of healthcare centers and central hospitals face recurring medicine shortages, impacting both hospital operations and patient care. Surgical procedures are curtailed due to chemical and equipment scarcities, while patients must seek medications outside hospitals, often without insurance coverage.

While administrative inefficiencies and policies contribute to the crisis, pharmaceutical companies are not mere bystanders. Each company holds a responsibility to contribute positively, enhancing their internal systems to ensure smooth operations. To maintain consistent healthcare supply, companies must implement robust forecasting systems, analyzing factors causing inaccuracies and proactively addressing hindrances for optimal performance.

Forecasting errors of the current forecasting model of the case-study company over the years are significantly high (Figure 2). Consequently, there are questions on which product line contributes largest to the forecasting error, the causes, and the most suitable forecasting model.

	2022													2023
MAPE	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	MAPE 2022	Jan
ALPHACHOAY	16%	21%	44%	45%	9%	19%	4%	34%	39%	38%	9%	31%	28%	48%
APROVEL	2117%	10%	461%	117%	61%	703%	27%	87%	348%	40%	110%	61%	112%	11%
CO APROVEL	63%	87%	145%	27%	42%	19%	54%	231%	79%	21%	24%	33%	63%	10%
CORDARONE	36%	25%	180%	30%	31%	13%	27%	38%	9%	26%	5%	48%	30%	24%
DEPAKINE	47%	24%	66%	9%	28%	20%	46%	17%	24%	10%	78%	98%	37%	182%
DUOPLAVIN	39%	1%	533%	591%	51%	43%	38%	76%	275%	26%	52%	14%	61%	228%
ELOXATINE	82%	32%	77%	36%	35%	47%	34%	74%	17%	32%	204%	39%	48%	55%
LOVENOX	56%	32%	7%	969%	211%	82%	303%	234%	128%	48%	8%	39%	71%	45%
PLAVIX	34%	9%	70%	24%	76%	51%	15%	124%	27%	18%	71%	71%	42%	29%
TARGOSID	37%	76%	0%	0%	208%	85%	56%	60%	147%	25%	48%	757%	93%	37%
TAVANIC	19%	46%	43%	5%	59%	36%	1499%	54%	25%	56%	37%	75%	50%	50%
TAXOTERE	113%	661%	21%	38%	24%	31%	34%	23%	44%	65%	71%	32%	49%	97%
XATRAL	36%	26%	148%	57%	34%	36%	31%	152%	113%	155%	43%	9%	51%	40%
EM	29%	23%	46%	54%	34%	30%	26%	45%	43%	37%	22%	41%	36%	50%
APIDRA	63%	27%	37%	40%	91%	14%	13%	54%	83%	97%	48%	39%	48%	29%
LANTUS	39%	18%	73%	20%	26%	13%	23%	42%	14%	16%	120%	53%	32%	29%
TOUJEO	33%	25%	5%	95%	25%	6%	22%	1%	4%	15%	38%	51%	23%	4%
Diabetes	42%	20%	59%	25%	29%	13%	23%	40%	17%	22%	84%	50%	33%	26%
FLAGYL	47%	17%	12%	21%	10%	7%	8%	9%	0%	17%	6%	17%	16%	7%
Outsourced	47%	17%	12%	21%	10%	7%	8%	9%	0%	17%	6%	17%	16%	7%
CEM	32%	23%	44%	46%	30%	27%	24%	42%	38%	35%	21%	37%	34%	48%
A class	26%	21%	43%	52%	27%	27%	19%	43%	40%	37%	20%	38%	33%	47%
Exclude A class	51%	28%	48%	36%	36%	27%	35%	38%	28%	26%	22%	35%	34%	56%
B Class	42%	22%	38%	25%	27%	12%	26%	31%	15%	25%	17%	24%	26%	67%

Figure 2. Many forecasts of different product lines exceed 30% error (highlighted in Red.)

1.1 Objectives

The objective of this paper is to reduce the forecasting error of target products of the pharmaceutical company to less than 30%. Successful findings not only benefit the company in production planning and sales, but also assure sufficient and in-time medical supply to hospitals and patients.

2. Literature Review

Forecasting is an important task in many areas of research and industry, ranging from economics and finance to engineering and supply chain management. Accurate forecasts can help decision-makers to better allocate resources, manage risks, and improve performance. Therefore, there is a growing interest in developing and applying advanced forecasting methods that can capture the complex patterns and dynamics of time series data.

2.1 Data processing

Empirical mode decomposition (EMD) is a signal processing technique that decomposes a signal into its intrinsic mode functions (IMFs) and a residual component. The IMFs represent the different frequency components of the signal, while the residual captures the high-frequency noise. EMD has been used in various applications, including heart rate variability analysis (Queyam et al. 2017) and time series forecasting (Büyükşahin & Ertekin 2019). In heart rate variability analysis, EMD was used to quantify fetal and maternal heart rates from abdominal ECG signals. In time series forecasting, EMD was combined with a new ARIMA-ANN hybrid method to improve forecasting accuracy. EMD has proven to be a versatile and effective technique for signal processing and analysis. While they evaluate their method's performance on several datasets, they do not compare it with other existing methods or conduct a comprehensive analysis of its strengths and weaknesses. This report aims to use EMD to extract linear and non-linear patterns from a set of data to apply relevant methods.

2.2 Time Series Methods

In time series forecasting, the moving average technique stands as a common approach, effectively smoothing data volatility and identifying trends. It involves averaging a rolling window of data points, with the window's size tailored to the data's underlying patterns. Originating in economics, moving average found utility in various fields like finance (Liu et al. 2020), healthcare (Liu et al. 2016), and energy (Wang et al. 2019). Its simplicity and versatility make it a popular choice, although its straightforwardness can occasionally be limiting when handling complex or erratic time series data.

To overcome these limitations, extensions to the basic moving average have emerged. ARIMA (Autoregressive Integrated Moving Average) is a noteworthy example, renowned for its wide application. By combining autoregression (AR), differencing (I), and moving average (MA) components, ARIMA adeptly captures linear dependencies and stationarity. This method has demonstrated its prowess in domains such as sales, stock price prediction, and weather forecasting. For instance, Zhao and Wang (2014) applied ARIMA to forecast the crude oil price, while Jamil (2020) used ARIMA to predict hydroelectricity consumption.

Another approach within this paper is exponential smoothing, a technique emphasizing recent observations while diminishing the weight of older ones. Despite its simplicity, constant updates from researchers have enhanced its performance. De Livera et al. (2011) introduced a state space modeling framework capable of addressing diverse characteristics through exponential smoothing.

Building on simple exponential smoothing, Holt's trend method injects a linear trend into the forecasting model. It shines when the time series exhibits trends without seasonality. Holt (1957) expanded the concept of basic exponential smoothing to accommodate the prediction of data that incorporates a trend.

In summary, time series forecasting leverages the moving average technique and the potent ARIMA method. While moving average's simplicity and adaptability are notable, ARIMA's prowess in capturing linear dependencies and stationarity elevates its utility. The integration of Holt's trend method provides enhanced trend analysis. These techniques together contribute to a robust toolkit for addressing time series forecasting challenges.

2.3 Machine learning methods

As machine learning has been used ubiquitously recently, SVR has gained popularity as a machine learning method that can capture both linear and non-linear dependencies in data. SVR models are based on the idea of mapping the input data to a higher-dimensional space using a kernel function, and then finding the optimal hyperplane that separates the data into two classes with the largest margin. A thorough investigation into each type of SVR was introduced to compare the forecast accuracy among SVR methods (Claveria & Torra 2015).

2.4 Ensemble methods
In order to improve forecasting accuracy, researchers have proposed various hybrid methods that combine two or more forecasting models. For example, ARIMA-Holt-Winters hybrid models have been used to capture both the linear and seasonal patterns of data (Bharti and Taneja 2015) while ARIMA-SVR hybrid models have been used to capture both the autoregressive and non-linear dependencies of data (Kavousi-Fard and Kavousi-Fard 2013). These hybrid models have shown promising results in terms of accuracy and robustness and have attracted much attention in both academia and industry. The concept of ensemble applied to the time series forecasting using SVR was conducted by Yildirim et al. (2015). The authors proposed an ensemble of SVR models based on different kernel functions and regularization parameters and showed that the ensemble approach outperformed individual SVR models on several real-world time series datasets. Another ensemble model of SVR is the integration with time series forecasting and deep learning using a heterogeneous approach (Kilimci et al. 2019). In addition, Büyükşahin & Ertekin (2019) also suggested a new hybrid model used to extract the advantages of each forecasting method for linear and non-linear data.

Overall, this research indicates that when compared to individual models or alternative ensemble approaches, ensemble methods of SVR and time series forecasting may greatly increase the accuracy and resilience of forecasts. In order to fully understand the benefits and drawbacks of various ensemble approaches in various contexts, more study is required. The specific methodology taken may depend on the type of time series data being utilized and the issue at hand.

3. Methods
In the course of this research, a range of methods and their associated limitations have been assessed, with the aim of identifying effective approaches and avoiding potential pitfalls for the current investigation. The evaluation of individual techniques, including ARIMA, Holt's trend, and SVR, highlights that each bears constraints that might compromise accuracy, especially in the face of complex data patterns. The emergence of ensemble approaches, however, has offered a solution by integrating multiple techniques to enhance forecast precision and reliability. By thoughtfully considering the merits and drawbacks of these methods, an effort is being made to arrive at a well-informed choice in crafting an effective ensemble strategy involving Support Vector Regression (SVR) for time series forecasting.

Table 1. Approach comparison based on a certain number of traits

Method	Type	Complexity	Ability to handle seasonality	Ability to handle trend	Ability to handle outliers	Suitable for large datasets
Holt's Trends	Statistical	Low	Good	Good	Poor	Yes
ARIMA	Statistical	Medium	Good	Good	Good	Yes
SVR	Machine Learning	High	Good	Good	Good	No

These are the three fundamental papers that are incorporated into my research. Kilimci et al. (2019) present a demand forecasting model for supply chain management, leveraging deep learning techniques such as CNNs and LSTM networks. The model combines forecasts from different methods, enhancing accuracy. However, its lack of comprehensive comparison with other deep learning models limits assessment. Büyükşahin and Ertekin (2019) propose an innovative hybrid forecasting method employing EMD, ARIMA, and ANN models, enabling the capture of both linear and nonlinear patterns. Yet, the method's computational intensity and lack of broader comparisons hinder its broader applicability assessment. Claveria et al. (2015) introduce SVR-based regional forecasting for Spain, demonstrating its accuracy and providing a performance analysis against alternative methods. However, the absence of specific model parameters and the paper's Spain-focused approach could limit replicability and generalization.

Table 2. A summary of the three key paper references and this paper

Key references	Methodology	Type of Data	Accuracy Metric	Results
Büyükşahin & Ertekin (2019)	ARIMA-ANN Hybrid + EMD	Time Series	RMSE	Improved accuracy compared to traditional methods
Claveria, Monte & Torra (2015)	SVR	Time Series	MAE, MAPE	Accurate for short-term forecasting, but may not perform well for long-term forecasting
Kilimci et al. (2019)	Deep Learning + Decision Integration	Supply Chain Data	MAPE	Outperformed traditional methods in terms of forecasting accuracy
This paper	Time series methods + SVR + ensemble	Time Series	MAPE	Ensemble methods outperformed individual methods in terms of forecasting accuracy

The proposed model framework begins with the collection of data, followed by the application of ABC classifications to categorize products, with a focus on Class-A items for forecasting. Subsequently, the dataset is partitioned into training and test sets. Individual forecasting methods are then implemented to generate predictions for each product, with the Mean Absolute Percentage Error (MAPE) computed for the test set across each forecasting technique. Transitioning to the ensemble stage, the framework integrates Empirical Mode Decomposition (EMD) (Huang et al. (1998)) to decompose the data into Intrinsic Mode Functions (IMFs), with subsequent evaluation for linearity and non-linearity. IMFs are segregated into linear and non-linear categories. The model presents two ensemble scenarios: In the first case, linear IMFs align with ARIMA, while non-linear IMFs correspond to SVR RBF. In the second case, Holt's Trend addresses linear IMFs, and SVR RBF tackles non-linear IMFs. Following these ensemble approaches, the MAPE is computed, ultimately selecting the optimal MAPE for each product between the two scenarios. This ensemble technique is termed "homogeneous ensemble" due to its coherent integration of methods across both linear and non-linear domains. A Python code is applied to perform the calculation process of this framework.

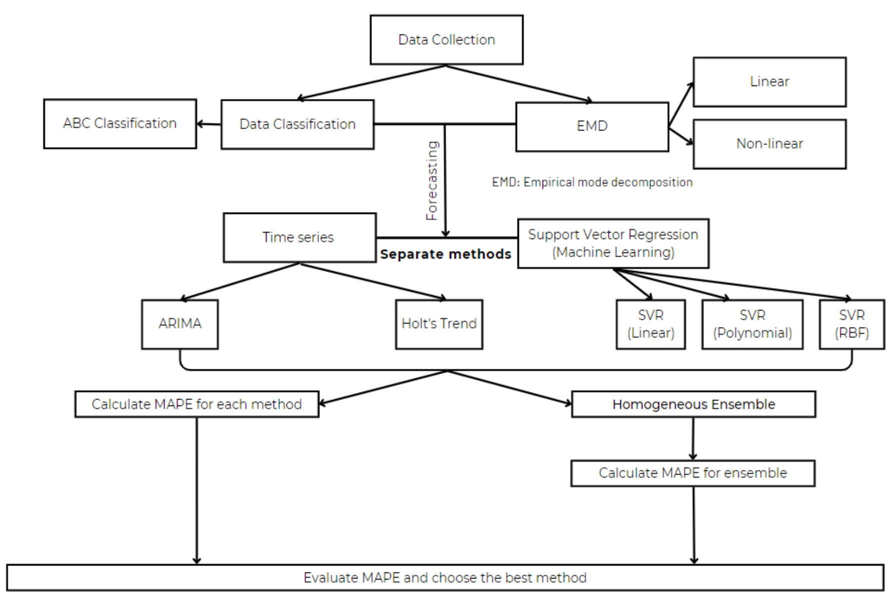

Figure 3. Model Framework

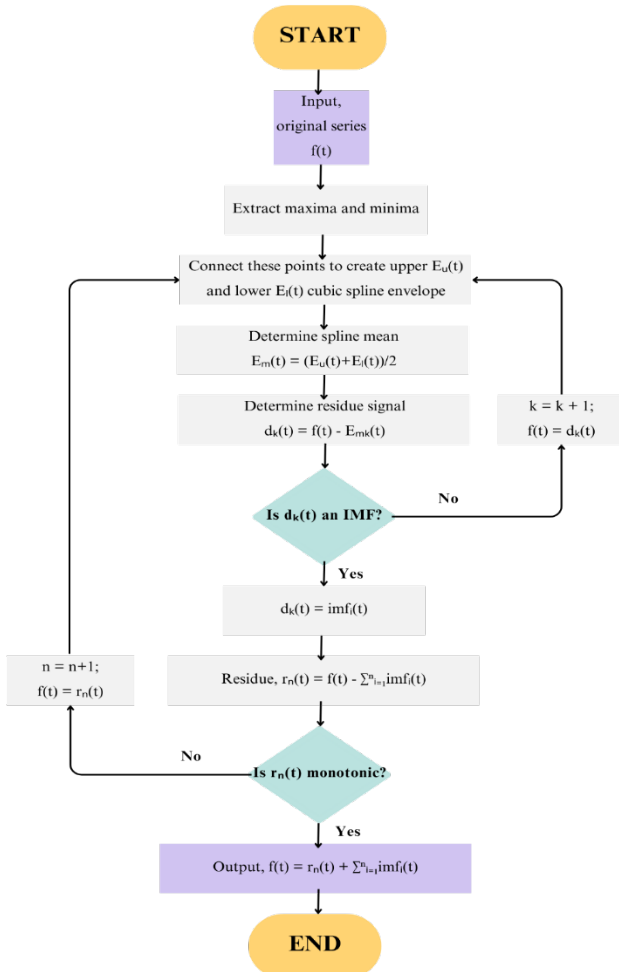

Figure 4. EMD flowchart

4. Data Collection

The monthly sales forecast from end customers is collected and cleaned. Next, A formula calculates the sale-in (from the company to distributors) demand from sales-out data, accounting for stock changes. An ABC classification identifies high-impact SKUs for forecasting. The data is split into train and test sets; the former trains the model, while the latter evaluates its performance using the mean absolute percentage error (MAPE). The model predicts the target variable for the input variables in the test set, and the predicted values are compared to the actual values. The "train set" includes figures from January 2015 to March 2022 (approximately 88% of the dataset), and the "test set" includes the remainders Keeping these sets separate prevents overfitting, ensuring the model's generalization. Each dataset's pattern, whether linear or non-linear, guides forecasting. Linear relationships entail proportional changes between variables, while non-linear ones involve non-proportional shifts, like exponential or polynomial functions. Non-linear relationships are more complex to model, accounting for components like seasonality, autocorrelation, and volatility.

Table 3. ABC Classification

GMID	Merging GMID	LMID	Products	Total SI/SKU	% Volume Contribution	Cummulative	Ranking	ABC Classification
693838	694211	345458	ALPHACHYMOTRYPSINE BOX 2 BL 15 TB VN	9,433,366	57.418%	57.418%	1	A
595210	595210	338235	FLAGYL 250MG TABCO BL2X10 M48	2,077,489	12.645%	70.063%	2	A
294508	294508	337126	PLAVIX 75MG TABCO BL14 M36 VN	1,066,016	6.489%	76.552%	3	A
254724	760295	348650	LOVENOX 4KIU/0.4ML INJ PS2 VN	858,185	5.224%	81.776%	4	A
190789	741838	322344	DEPAK CHRO500 333-145MG TABCR	530,878	3.231%	85.007%	5	A
609028	741644	339212	TAVANIC 500MG TABCO BL5 SWI VN	448,327	2.729%	87.736%	6	B
453737	740544	328207	DEPAKINE 200MG TABEC TB40 S3 M	433,132	2.636%	90.372%	7	B
599739	599739	338389	XATRAL 10MG TABCR BL1X30 S3 VN	316,429	1.926%	92.298%	8	B
356084	356084	331250	DUOPLAVIN 75-100MG TABCO BL3X1	262,052	1.595%	93.893%	9	B
323551	741878	322342	DEPAKINE 8G/40ML SOL BT1 S3 M3	228,009	1.388%	95.281%	10	B
254725	760297	348651	LOVENOX 6KIU/0.6ML INJ PS2 VN	144,786	0.881%	96.162%	11	C
191951	191951	322330	APROVEL 150MG TAB B/ 2BLS X 14 VN	133,936	0.815%	96.977%	12	C
301249	301249	318174	LANTUS 300IU/3ML INJ SOLO5 S3	116,969	0.712%	97.689%	13	C
581127	581127	337359	CORDARONE 200MG TAB BL2X15 VN	99,554	0.606%	98.295%	14	C
246070	246070	322333	COAPRO 150-12.5MG TABCO BL2X14	73,556	0.448%	98.743%	15	C
610632	610632	338530	LANTUS 1KIU/10ML INJ VL1 M24 V	32,787	0.200%	98.943%	16	C
623105	623105	343013	TARGOSID 400MG/6ML INJPO VLSX1	24,401	0.149%	99.091%	17	C
692394	692394	345362	TOUJEO 450IU/1.5ML M30 VN	22,484	0.137%	99.228%	18	C
188480	188480	322336	CORDARONE 150MG/3ML INJ AM6 VN	21,407	0.130%	99.358%	19	C
301250	301250	318175	APIDRA 300IU/3ML INJ SOLO5 S3	20,969	0.128%	99.486%	20	C
509960	509960	331153	TAXOTERE 20MG/1ML INJ VL1 M24	18,892	0.115%	99.601%	21	C
191952	191952	322331	APROVEL 300MG TABCO BL2X14 RM	15,485	0.094%	99.695%	22	C
514870	514870	331578	COAPRO RM 300-12.5MG TABCO BL2	12,661	0.077%	99.772%	23	C
509958	509958	331156	ELOXATINE 100MG/20ML INJ VL1 M	11,952	0.073%	99.845%	24	C
628666	628666	340567	TAXOTERE 80MG/4ML INJ VL1 M24	11,333	0.069%	99.914%	25	C
509959	509959	331155	ELOXATINE 50MG/10ML INJ VL1 M2	10,298	0.063%	99.977%	26	C
785876	785876	338789	SOLIQUA 300IU/ INJ SOLO3 PEA M24XC	1,440	0.009%	99.985%	27	C
673667	673667	347990	MYOZYME 50MG INFLS VL1 VN	1,140	0.007%	99.992%	28	C
340430	340430	322354	PLAVIX 300MG TABCO BL3X10 M36	837	0.005%	99.997%	29	C
316895	316895	322335	COAPRO 300-25MG TABCO BL2X14 M	419	0.003%	100.000%	30	C

The chosen class-A products include Alpha, Flagyl, Plavix 75, Depak Chrono, and Lovenox 4KIU, which contributes to the sale volume the most.

5. Results and Discussion

5.1 Individual methods

Table 4. Results of Holt's Trend

Exponential Smoothing	Date	Depak Chrono	Flagyl	Alpha	Plavix 75	Lovenox 4KIU
Holt's Trends	Apr-22	8153.57	2947.75	41591.35	29219.05	17116.29
	May-22	7427.24	2959.13	42215.52	29690.25	15871.39
	Jun-22	6700.90	2970.51	42839.68	30161.46	14626.50
	Jul-22	5974.56	2981.89	43463.85	30632.66	13381.61
	Aug-22	5248.22	2993.27	44088.02	31103.86	12136.71
	Sep-22	4521.88	3004.66	44712.18	31575.06	10891.82
	Oct-22	3795.54	3016.04	45336.35	32046.26	9646.93
	Nov-22	3069.21	3027.42	45960.52	32517.47	8402.03
	Dec-22	2342.87	3038.80	46584.68	32988.67	7157.14
	Jan-23	1616.53	3050.18	47208.85	33459.87	5912.25
	Feb-23	890.19	3061.56	47833.02	33931.07	4667.35
	Mar-23	163.85	3072.95	48457.19	34402.28	3422.46
MAPE		53.00%	12.00%	9.00%	13.00%	48.00%

Table 5. Results of ARIMA

ARIMA	Date	Depak Chrono	Flagyl	Alpha	Plavix 75	Lovenox 4KIU
	Apr-22	6415.69	2831.41	44119.37	30339.27	16984.36
	May-22	7055.96	2858.49	45260.42	30678.24	10285.06
	Jun-22	5951.39	2885.58	45308.66	31017.20	10285.06
	Jul-22	5960.41	2912.66	45418.65	31356.16	10285.06
	Aug-22	5232.20	2939.75	45171.96	31695.12	10285.06
	Sep-22	4965.16	2966.83	45304.53	32034.08	10285.06
	Oct-22	4383.32	2993.92	45274.98	32373.04	10285.06
	Nov-22	3989.12	3021.00	45286.66	32712.01	10285.06
	Dec-22	3457.25	3048.09	45270.02	33050.97	10285.06
	Jan-23	2998.33	3075.17	45282.01	33389.93	10285.06
	Feb-23	2475.98	3102.26	45277.29	33728.89	10285.06
	Mar-23	1978.52	3129.34	45279.03	34067.85	10285.06
MAPE		58.00%	12.00%	8.00%	13.00%	31.00%

In the context of individual method forecasting, the analysis reveals that among the products, namely Flagyl, Alpha, and Plavix 75, Alpha stands out with the lowest MAPE value across both cases. Conversely, the product Depak Chrono consistently exhibits a high MAPE exceeding 30%. In terms of forecasting methods, the ARIMA approach demonstrates superior performance across most products, with the exception of depak chrono, where ARIMA fares better than Holt's trend method.

Table 6. Comparisons between the forecasted MAPE and the original MAPE

SKU	Most Improved MAPE	MAPE without forecasting methods	Improvement compared to Lowest MAPE
Depak Chrono	53.00%	51.00%	-3.92%
Flagyl	12.00%	17.00%	29.41%
Alpha	8.00%	31.00%	74.19%
Plavix 75	13.00%	36.00%	63.89%
Lovenox 4KIU	31.00%	86.00%	63.95%

Upon contrasting the optimized MAPE results from the chosen individual method with the original non-forecasted data, a noteworthy pattern emerges. Among the products, Alpha stands out as the most enhanced, indicating substantial improvement. Plavix 75 and Lovenox 4KIU also exhibit considerable enhancement. However, Depak Chrono presents a contrasting scenario with a negative shift, suggesting a regression from the original data.

5.2 Ensemble methods

Table 7. Results of homogeneous ensemble

Methods	Date	Depak Chrono	Flagyl	Alpha	Plavix 75	Lovenox 4KIU
Linear: Holt's Trend Non-Linear: SVR RBF (Stopping boundary: 0.1)	Apr-22	8474.31	2953.91	40559.83	39067.05	7594.04
	May-22	9255.43	2960.55	40703.67	39506.83	7688.20
	Jun-22	10036.55	2967.42	40845.75	39946.57	7782.36
	Jul-22	10817.67	2974.39	40988.07	40386.29	7876.51
	Aug-22	11598.80	2981.36	41131.35	40826.01	7970.67
	Sep-22	12379.92	2988.34	41275.42	41265.74	8064.83
	Oct-22	13161.04	2995.32	41419.93	41705.46	8158.98
	Nov-22	13942.16	3002.30	41564.61	42145.18	8253.14
	Dec-22	14723.28	3009.28	41709.34	42584.90	8347.30
	Jan-23	15504.40	3016.26	41854.09	43024.62	8441.45
	Feb-23	16285.52	3023.24	41998.83	43464.34	8535.61
	Mar-23	17066.64	3030.22	42143.58	43904.07	8629.77
MAPE		55.04%	7.15%	4.71%	58.93%	4.24%
	Date	Depak Chrono	Flagyl	Alpha	Plavix 75	Lovenox 4KIU
Linear: ARIMA Non-Linear: SVR RBF (Stopping boundary: 0.1)	Apr-22	9612.23	2803.13	40453.22	34840.20	7695.39
	May-22	8408.02	2822.80	40584.03	35081.88	7697.66
	Jun-22	8153.77	2842.38	40723.44	35323.33	7700.10
	Jul-22	8962.40	2861.90	40870.51	35564.51	7702.72
	Aug-22	8865.25	2881.43	41025.84	35805.49	7705.51
	Sep-22	8564.81	2900.98	41189.16	36046.35	7708.47
	Oct-22	8760.85	2920.55	41360.57	36287.16	7711.59
	Nov-22	8917.17	2940.12	41539.96	36527.94	7714.89
	Dec-22	8826.88	2959.70	41727.37	36768.72	7718.35
	Jan-23	8838.95	2979.28	41922.77	37009.49	7721.98
	Feb-23	8941.17	2998.86	42126.17	37250.27	7725.77
	Mar-23	8964.33	3018.45	42337.57	37491.05	7729.73
MAPE		7.62%	8.01%	4.74%	38.57%	9.09%

Flagyl, alpha, and Lovenox exhibit relatively consistent MAPE values in both scenarios of the ensemble method involving Holt's trend and ARIMA. However, the Holt's trend ensemble approach showcases a marginal increase in MAPE compared to the alternative. Conversely, Depak Chrono and Plavix 75 demonstrate substantial increases in MAPE when subjected to the ensemble method with ARIMA. Notably, among all the products, Lovenox 4KIU boasts the lowest MAPE.

Table 8. Comparisons between the forecasted MAPE and the original MAPE

SKU	Most Improved MAPE	MAPE without forecasting methods	Improvement compared to Lowest MAPE
Depak Chrono	7.62%	51.00%	85.06%
Flagyl	7.15%	17.00%	57.94%
Alpha	4.71%	31.00%	84.81%
Plavix 75	38.57%	36.00%	-7.14%
Lovenox 4KIU	4.24%	86.00%	95.07%

The heterogeneous method demonstrates a remarkable shift in MAPE, displaying significant enhancements for all products except Plavix 75. The lack of improvement in the case of Plavix 75 is attributed to an unsuitable stopping criterion employed in the EMD process, which will be elaborated upon in the subsequent section. Lovenox 4KIU shows the highest improvement with 95.07% deduction in the MAPE.

5.3 Proposed Improvements

As mentioned above, Plavix 75 had a negative shift in the MAPE due to the inappropriate use of the stopping criterion, which can be improved through the sensitivity analysis in this part. In the sensitivity analysis of the homogeneous ensemble method, various stopping boundaries (0.01, 0.02, 0.05, 0.1, 0.2, 0.5, and 0.9) are examined to gauge their impact on forecast accuracy. The stopping boundary is pivotal in the Empirical Mode Decomposition (EMD) algorithm, dictating when the decomposition should halt. The code employs a stopping boundary value as a threshold, determining IMF extraction cessation based on the sum of absolute signal values. This choice is contingent upon the dataset, signal traits, and desired decomposition depth, with lower values capturing finer details and higher ones revealing broader trends. Performing a sensitivity analysis aids in selecting the most fitting threshold for the EMD algorithm, supported by domain knowledge and dataset specifics. The homogeneous ensemble combines Holt's Trend and RBF SVR, and ARIMA and RBF SVR methods in a consistent pattern, bolstering model dependability.

Table 9. MAPE comparison for each stopping criterion

Stopping criteria	Depak Chrono (Holt's Trend)	Depak Chrono (ARIMA)	Flagyl (Holt's Trend)	Flagyl (ARIMA)	Alpha (Holt's Trend)	Alpha (ARIMA)	Plavix 75 (Holt's Trend)	Plavix 75 (ARIMA)	Lovenox 4KIU (Holt's Trend)	Lovenox 4KIU (ARIMA)
0.01	64.07%	13.33%	4.88%	2.32%	1.82%	1.69%	67.76%	46.30%	21.82%	28.00%
0.02	62.71%	12.43%	4.03%	1.82%	0.83%	0.70%	66.43%	45.15%	15.69%	23.35%
0.05	55.04%	7.62%	2.37%	1.51%	1.24%	1.27%	63.84%	42.89%	9.80%	17.26%
0.1	55.04%	7.62%	7.15%	8.01%	4.71%	4.74%	58.93%	38.57%	4.24%	9.09%
0.2	48.46%	4.85%	7.15%	8.01%	10.80%	11.91%	35.11%	18.03%	5.03%	7.32%
0.5	45.72%	15.03%	7.15%	8.01%	10.80%	12.83%	7.82%	10.11%	40.79%	21.38%
0.9	45.72%	15.03%	7.15%	8.01%	10.80%	12.83%	7.82%	10.11%	40.79%	21.38%

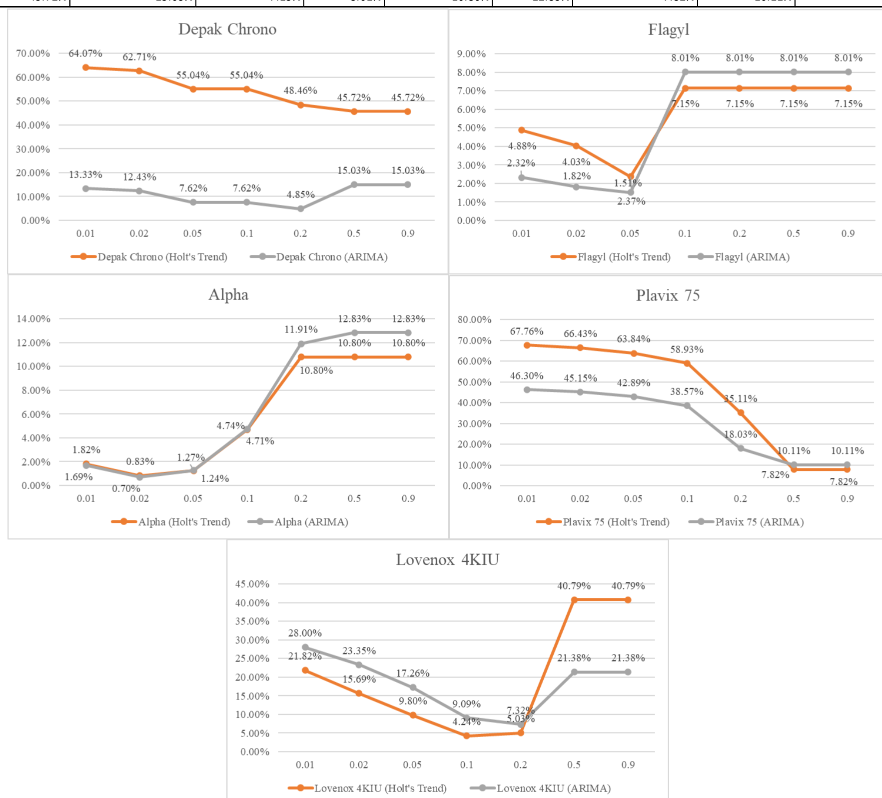

Figure 5. MAPE alternation with different stopping criteria for Plavix 75 for each product

Results analysis indicates that increasing the stopping boundary eventually leads to stable MAPE values, signifying the effective decomposition threshold being reached. Notably, Alpha and Plavix 75 react distinctively to this criterion. Alpha's MAPE values rise with higher stopping criteria, indicating less accurate forecasting with extensive decomposition. Conversely, Plavix 75's MAPE values decrease, suggesting better accuracy with increased decomposition. Although Plavix 75 showed no improvement at a stopping criterion of 0.1, evaluating various criteria reveals a notable 7.82% enhancement. Flagyl and Lovenox 4KIU follow similar patterns, experiencing decreasing MAPE values until a threshold, then increasing. Depak Chrono exhibits a nuanced pattern, with the Holt's Trend method showing its lowest peak after 0.5, and the ARIMA and RBF SVR model peaking at 0.2. This divergence stems from dataset characteristics. The homogeneous ensemble method impresses with strong MAPE results, aligned with dataset traits. Sensitivity analysis underscores the significance of appropriate EMD boundary selection on forecast accuracy, varying by pharmaceutical product.

5.4 Validation

Table 10. Final result comparisons

SKU	No forecasting method	Individual	Homogeneous	Highest Improvement %
Depak Chrono	51%	53.00%	4.85%	90.49%
Flagyl	17%	12.00%	1.51%	91.12%
Alpha	31%	8.00%	0.70%	97.74%
Plavix 75	36%	13.00%	7.82%	78.28%
Lovenox 4KIU	86%	31.00%	4.24%	95.07%

The provided table reaffirms that selecting the appropriate stopping criterion in EMD can indeed enhance forecast accuracy within the homogeneous approach. This is evidenced by the significant improvement in Plavix 75's MAPE achieved through the right choice. Furthermore, the homogeneous ensemble's remarkable outcome validates the initial hypothesis that this method outperforms individual approaches by capitalizing on diverse forecasting strengths and data characteristics.

6. Conclusion

This paper aimed to address the forecasting challenges in the pharmaceutical industry by exploring and evaluating various forecasting methods. Through a comprehensive analysis of individual forecasting methods and the development of a ensemble approach, valuable insights and improvements in forecast accuracy have been achieved. The analysis of individual forecasting methods highlighted the importance of selecting appropriate methods based on the characteristics of the data and the underlying patterns. The findings emphasized the need to consider factors such as linearity, trend, and non-linear patterns when choosing the most effective forecasting method for each product.

The homogeneous ensemble approach, specifically by adjusting the stopping boundaries for the Empirical Mode Decomposition process and aligning it with the specific characteristics of the data, the homogeneous ensemble achieved the most optimal MAPE. This underscores the significance of adjusting the stopping boundaries appropriately to extract relevant linear and non-linear patterns for improved forecasting accuracy.

In summary, this paper contributes to advancing forecasting practices in the pharmaceutical industry by providing valuable insights and practical frameworks for enhancing forecast accuracy. The findings have important implications for decision-making and strategic planning in the pharmaceutical sector, enabling more informed and accurate demand forecasting.

It is important to acknowledge that forecasting is an ongoing process, and there is always room for further refinement and improvement. As a recommendation, it is crucial for future research to address the limitations posed by the limited availability of data for model training in this study. The dataset used here covers a short period, which may restrict the models' ability to capture long-term trends and account for unforeseen patterns that could emerge in the future. To enhance the forecasting models' accuracy and generalizability, researchers should aim to collect more extensive and diverse datasets. Including data from a broader timeframe and covering a wider range of scenarios and market conditions can improve the models' robustness and applicability. Moreover, incorporating data from different geographical regions or market segments can help address potential biases and further validate the models' effectiveness in various contexts. Furthermore, it is essential to explore and integrate additional data sources that may provide valuable insights into the pharmaceutical industry's demand dynamics. This could include external factors such as macroeconomic indicators, regulatory changes, public health events, and other relevant variables that influence drug demand. Leveraging such data can enrich the forecasting models and enable them to adapt to dynamic and evolving market conditions. Moreover, the use of advanced machine learning techniques and artificial intelligence algorithms should be considered in future research. These approaches have the potential to extract more complex patterns and relationships from the data, leading to more accurate and robust forecasting models.

Overall, this research enhances the understanding of forecasting methodologies in the pharmaceutical industry, enabling more accurate and informed decision-making, and ultimately improving operational efficiency and patient care.

References

Bharti, P. and Taneja, V., Forecasting of Indian monsoon rainfall using ARIMA-Holt-Winters hybrid models. *International Journal of Engineering Research and Applications*, 5(12), 6-11, 2015.

Büyükşahin, Ü. Ç. and Ertekin, Ş., Improving forecasting accuracy of time series data using a new ARIMA-ANN hybrid method and empirical mode decomposition. *Neurocomputing*, 361, 151–163, 2019 https://doi.org/10.1016/j.neucom.2019.05.099.

Claveria, O. and Torra, S., *"Regional Forecasting with Support Vector Regressions: The Case of Spain."* www.ub.edu/aqr/Reimer, D., Entrepreneurship and Innovation, Available: http://www.ieomsociet.org/ieom/newsletters/, July 2020.

De Livera, A. M., Hyndman, R. J. and Snyder, R. D., Forecasting time series with complex seasonal patterns using exponential smoothing. *Journal of the American statistical association*, 106(496), 1513-1527, 2011.

Holt, C. C., Forecasting trends and seasonals by exponentially weighted moving averages. *ONR Research Memorandum*, Carnegie Institute of Technology, 1957.

Huang, N. E., Shen, Z., Long, S. R., Wu, M. C., Shih, H. H., Zheng, Q. and Liu, H. H., The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. *Proceedings of the Royal Society of London. Series A: mathematical, physical and engineering sciences*, *454*(1971), 903-995, 1998.

Home. Health at a Glance 2021 : OECD Indicators | OECD iLibrary. (n.d.). https://www.oecd-ilibrary.org/sites/e26f669cen/index.html?itemId=%2Fcontent%2Fcomponent%2Fe26f669c-en

Jamil, R., Hydroelectricity consumption forecast for Pakistan using ARIMA modeling and supply-demand analysis for the year 2030. *Renewable Energy*, 154, 1-10, 2020.

Kavousi-Fard, A. and Kavousi-Fard, F., A new hybrid correction method for short-term load forecasting based on ARIMA, SVR and CSA. *Journal of Experimental & Theoretical Artificial Intelligence*, 25(4), 559-574, 2013.

Kilimci, Z. H., Akyuz, A. O., Uysal, M., Akyokus, S., Uysal, M. O., Atak Bulbul, B., Ekmis, M. A. and Silva, T. C., An improved demand forecasting model using deep learning approach and proposed decision integration strategy for supply chain. *Complexity*, 2019. https://doi.org/10.1155/2019/9067367

Liu, S., Wang, L. and Yang, X., Healthcare demand forecasting based on a hybrid method of multiple linear regression with stepwise selection, support vector regression and the bat algorithm. *International Journal of Environmental Research and Public Health*, 13(11), 1071, 2016.

Queyam, Abdullah and Pahuja, Sarwan and Dahiya, Dilbag., Quantification of Feto-Maternal Heart Rate from Abdominal ECG Signal Using Empirical Mode Decomposition for Heart Rate Variability Analysis. *Technologies*. 5. 68. 10.3390/technologies5040068, 2017.

State governments spending the most on health care - self. Self. (2022, January 12). https://www.self.inc/blog/state-governments-spending-the-most-on-health-care

Wang, W. chuan, Chau, K. wing, Xu, D. mei and Chen, X. Y., Improving Forecasting Accuracy of Annual Runoff Time Series Using ARIMA Based on EEMD Decomposition. *Water Resources Management*, 29(8), 2655–2675, 2015, https://doi.org/10.1007/s11269-015-0962-6

Wold, H., *A study in the analysis of stationary time series* (Doctoral dissertation, Almqvist & Wiksell), 1938.

Yildirim, T., Özkan, G. and Baş, Ü., A novel hybrid ensemble approach based on support vector regression for time series forecasting. *Neurocomputing*, 149, 641-649, 2015.

Zhao, C. L. and Wang, B., Forecasting crude oil price with an autoregressive integrated moving average (ARIMA) model. *Fuzzy information & engineering and operations research & management*, 275-286, 2014.

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