ARIMAX Model for Forecasting Maintenance Work (AMFM): A Multi-Stage Seasonal ARIMAX Model for Workorder Time Series Forecasting

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Abstract

E-commerce business depends on smooth day to day functioning of it's warehouses/facilities. The functioning of these facilities depend on the health of material handling equipment. To keep these equipment healthy, these facilities employ the help of maintenance engineers who perform predictive/breakdown maintenance work. To ensure an effective maintenance operation necessitates efficient planning of maintenance work. For efficient planning of future maintenance work, one needs to have good estimates of the future maintenance work. We created time series of maintenance work (breakdown and miscellaneous) in terms of demand hours for every day/week. Next, we built several models and evaluated these models on the basis of forecasting accuracy metrics viz. Mean Absolute percent error (MAPE) and Root mean squared error (RMSE) to determine which modelling technique is most suitable. Seasonal ARIMA with exogenous variable (SARIMAX) was found to be the most suitable approach with additional hyperparameters like training dataset length and training data window start/end. This paper discusses the details of this SARIMAX approach and the procedure used to identify the best facility specific SARIMAX model. The proposed solution provides forecasts using SARIMAX framework with an out of sample MAPE less than 30 percent and RMSPE less than 20.

1 Introduction

Time series forecasting has been integral part of data science and statistics with the earliest applications in the area of production planning and control, weather and stock market forecasting [1, 2]. Time series analysis and forecasting as a field dates back to the early 1930s [3]. Forecasting has been used for pretesting market launch of new products [4, 5, 6, 7, 8]. Benefits of integrated business planning, forecasting, and process management has been demonstrated by Toor et. al. [9]. Application of demand Forecasting for e-commerce Platforms has also been attempted in past [10, 11]. However, forecasting maintenance engineering work for e-commerce facilities using time series data has not been reported yet.

Scheduling and forecasting maintenance work is a critical problem in the world of maintenance engineering, but it is mostly done at an equipment level to predict equipment breakdown [12, 13, 14]. Historically, it has been solved using machine learning as well as classical time series forecasting techniques for facility and asset maintenance by various industrial software providers [15, 16, 17, 18]. Most industrial forecasting solutions are available as add on features in an Enterprise Asset Management Software and offer limited customization based on the business realities of the end user. Many of these solutions are tailored more towards needs of traditional manufacturing, aerospace and power-plant maintenance. Maintenance work prediction for electronics systems has been carried using SARIMA [14]. Similarly, predictive maintenance of production equipment has been reported using neural network autoregression and ARIMA [19, 20]. However, the varied nature/type and complexity of equipment in e-commerce facilities, with every facility being unique, necessitates the development of forecasting models which capture the facility specific business realities. For example, one facility may may differ from another in terms of its operational hours, available maintenance hours, type, nature and number of equipment as well as the days on which a facility is shut down owing to holidays. Hence, one needs to develop facility specific forecasting models to accurately predict maintenance activities in e-commerce facilities. Besides, these facilities keep changing with time due to dynamic nature of e-commerce business, which necessitates developing an approach which can help adapt to the new reality. Also, there is a lack of availability of standard methods to estimate/predict the number of hours required for

maintenance activities [21]. Forecasting model for maintenance and repair costs of buildings has been explored [22], also approaches for maintenance forecasting management have been explored [23]. However, scientific literature reporting development of forecasting maintenance work in the context of e-commerce facilities remains limited to internal consumption of operators of these facilities or does not exist. In this context, we are reporting a forecasting approach which we devised to suit the facility specific as well as dynamic (time dependent) nature of the e-commerce facilities. The findings from our investigation to forecast the maintenance work are discussed in detail by bringing out the comparison between different forecasting techniques. The proposed approach uses a grid of hyperparameters which include exogenous variables which influence the workorder generation process as well as hyperparameters that guide selection of the most appropriate training data.

Present day e-commerce facility process large volumes of customer orders everyday, which is only possible because of the high reliability of equipment supporting these facilities. The maintenance work pertaining to these equipment is digitally recorded as a workorder. The health of these equipment is taken care by facility maintenance teams by executing and planning/scheduling workorders (WOs) for thousands of equipment of different types every day. This maintenance work is divided into three major components: (1) scheduled and planned preventive maintenance, including planned repairs and shutdowns, and (2) emergency/breakdown maintenance and (3) miscellaneous. The first one is deterministic in nature, whereas the latter two depend on the probabilistic failure pattern and facility specific business reality. The latter two contribute to uncertainty in maintenance forecasting and capacity planning. In this work, we have gathered breakdown and miscellaneous maintenance WO time series as these are the ones that bring uncertainty in planning [24]. Each workorder (WO) requires a well defined number of maintenance hours to complete the maintenance of that equipment. This workorder hours demand across a span of time has been gathered and modelled as time series in the present work to forecast the demand of workorder hours for next 3 weeks. This forecast is essential in determining the number of maintenance hours required and available operational hours (Available Operational Hours = Total Hours - Maintenance Hours). Available operational hours in turn help the facility decide the shipment handling capacity as well as number of maintenance engineers required and configuration of day/night shifts. In the absence of this workorder hours forecast, these decisions remain ad-hoc and tempo-spatially specific in nature. As important facility specifications like shipment handling capacity and required number of maintenance engineers could not be updated periodically depending on changes in demand workorder hours. This leads to instances where demand for maintenance work is greater than available maintenance hours leading to delay in completion of workorders as well as leftover shipments which facility is unable to process. To bridge these gaps, one needs to pro-actively know the demand of workorders for each facility and accordingly plan [25].

Accurate maintenance forecasting has the potential to increase operational availability and reduce maintenance-related downtime [26]. WO forecasting also helps e-commerce business to pro-actively know the volume of maintenance work at facility level and then project the same for a cluster of co-located facilities.This in turn can help facilitate cluster level work aggregation for maintenance staff across the co-located facilities and realize associated efficiencies. This opens up the opportunity to move away from facility specific planning to network wide/centralized planning. Centralized planning using data driven insights can help create scenario specific plans by pro-actively adjusting maintenance hours availability across planning period for a group of sites ahead of time. An excess demand of maintenance WO hours can be fulfilled by extra maintenance hours available with another facility in the same cluster. Also, it makes workorder scheduling more accurate/ robust bringing uniformity in planning across multiple facilities in the network. Hence, we collected time series data of workorders for multiple facilities and developed a data driven solution which uses past 52 weeks data for forecasting the demand of workorders across these facilities for the following 3 weeks. This solution, namely an ARIMAX Model for Forecasting Maintenance Work (AMFM), provides the e-commerce facilities a visibility into future and plan as well prioritize high criticality maintenance work ahead of time.

2 Notation List

ACF: Autocorrelation Function

AIC: Akaike Information Criterion

BIC: Bayesian Information Criterion

MISC Miscellaneous Maintenance in Hours

PACF Partial Autocorrelation Function

WO Maintenance Work Order

MAPE Mean Absolute Percent Error

RMSPE Root Mean Squared Percent Error

3 Problem Statement

The primary problem we are solving through this work is to forecast workorders which contribute to the uncertainty in planning, namely the breakdown or reactive WOs as well as three other types of WOs called training, project and

admin (broadly classified as miscellaneous). Through active forecasting of Demand across these 4 workorder types, we envisage to drive data informed decisions to influence each facility's plan. The purpose of building the forecasting model is to ensure every facility has an accurate forecast for WO hours at a weekly frequency. To achieve this, we need to meet following objectives:

- Forecasting model needs to provide consistent forecast of WO hours (aggregate of different WO types) at a facility level.
- Approach needs to be accurate enough to have good out of sample accuracy as well as generalizable across multiple facilities
- Model shall be parsimonious and results explainable to facility planning teams

To meet the above objectives, we need to critically examine time series corresponding to each WO type as well as at an aggregate level and identify important features which influence the behaviour or movement of these time series.

4 Model Development

In the present work, we have developed a forecasting model inspired from the use case of maintenance work planning done in e-commerce facilities. The problem is to build facility specific forecasting models for multiple time series pertaining to different nature of workorders. The complexity of this effort is governed by the nature of facility specific business realities, eg. days/weeks on which there is sudden increase or drop in maintenance activities. There are both known unkowns and unkown unkowns which are to be identified and accounted for while selecting the most appropriate approach for forecasting. Besides, we are limited by the length of historic time series data which can be used to train the forecasting model. We cannot use data which is older than 1 year because the facilities undergo many changes every 4 quarters in terms of equipment and maintenance schedules due to the ever evolving nature of e-commerce facilities. Last but not the least, the forecast needs to be auto published every week by consuming streaming time series data. The forecast model also needs to be adaptively learn from any change in the business reality which governs the generation of WOs and accordingly adjusting the forecast model. We have documented the model development into multiple sections viz. data preparation, model creation, model testing and deployment (Section 4 and Section 5). Results are discussed in Section 6, followed by conclusions in Section 7.

4.1 Data Preparation

We picked time series data of different WO types from a dozen facilities and for each time series performed Augmented Dicky Fuller (ADF) [1] test to evaluate the stationary/ non-stationary nature of the time series. We also calculated rolling statistics (rolling mean and standard deviation). This revealed that some of the time series (Reactive-r, Project-p, Admin-a, Training-t, Billable- b= r+p+t) are stationary whereas others are non-stationary in nature, refer Figure 1. The non-stationary time series need to be made stationary by suitable differencing.

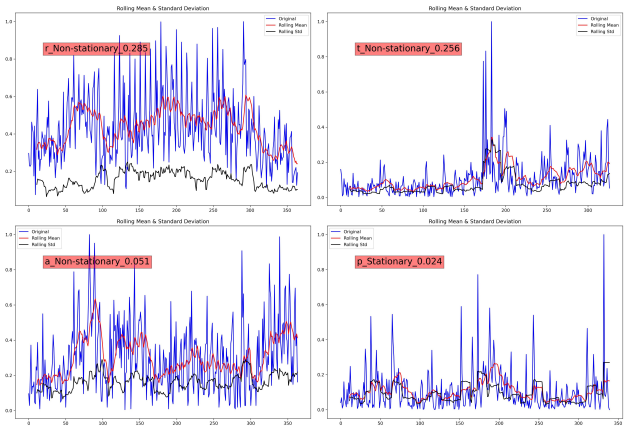

Figure 1: Results for site 1: Rolling Mean and Standard deviation for different Time series

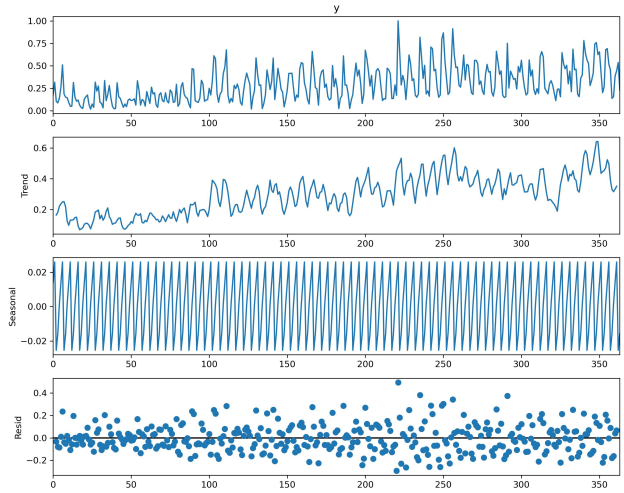

Figure 2: Results for site 1: Additive decomposition for Time series = 'b'

[1] Augmented Dickey Fuller test (ADF Test) is a common statistical test used to test whether a given Time series is stationary or not.

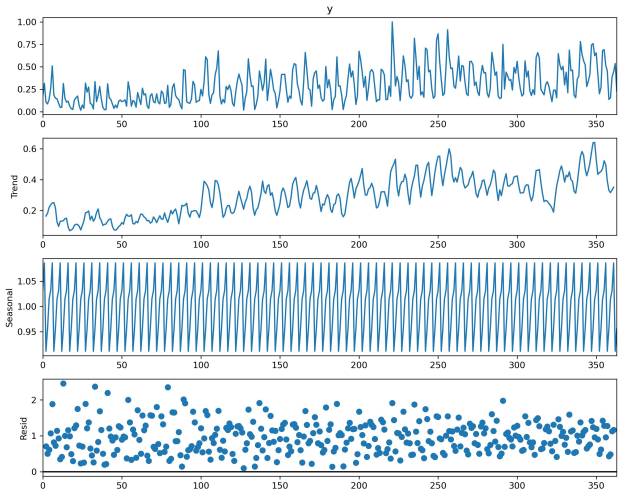

Figure 3: Results for site 1: Multiplicative decomposition for Time series = 'b'

4.2 Selection of Forecasting method

During preliminary modelling, we experimented with multiple approaches like TBATS, Simple Exponential Smoothing (SES), Auto Regressive Integrated Moving Average (ARIMA), Auto Regressive Integrated Moving Average with Exogenous variable (ARIMAX), Seasonal Auto Regressive Integrated Moving Average with Exogenous variable (SARIMAX) for daily as well weekly aggregated time series data. To date, these forecasting models have seen little use in the area of maintenance engineering and authors could not find use of these models in forecasting maintenance work for e-commerce facilities. We performed weekly aggregation of the daily WO time series data, however even after weekly aggregation some of these time series are stationary and some non-stationary. Among all the approaches investigated, SARIMAX resulted in better forecasting performance in terms of MAPE/RMSPE, as shown in Table 1.

SARIMAX model has been used for short-term load forecasting [27], decomposition method with SARIMAX model has been demonstrated to give low MAPE [28]. SARIMAX modeling has been used for electricity generation forecasting of grid-connected Photovoltaic (PV) plants [29] as well as for forecasting emergency department (ED) hourly occupancy [30]. Experimenting with both daily and weekly aggregated data, we found that daily data does not allow selection of a generalized forecasting method for all the 4-time series across different facilities. A deep dive with the facilities around the actual time series data for different WO types uncovered that WO hours are some times booked/logged into the system on just 1 day of the week and the day of the week when they get logged may also vary from one facility to another. This makes the daily data unreliable for training a forecasting model which is supposed to make daily prediction. Also, working backwards from the business requirement of a weekly forecast, it was decided to aggregate time series to transform daily data into weekly. Next we devised, a more advanced 2 stage SARIMAX has been developed to discover the best SARIMAX model for each site and time series. We have developed a tool around this model called ARIMAX Model for Forecasting Maintenance Work (AMFM). US holiday data has been used as exogenous variable used in the SARIMAX approach owing to the fact that during holiday period, the level of maintenance activity changes for the facilities. Besides, the selection of historic time series dataset is limited to last 365 days as the facility specific reality like the number of equipments and no of technicians (maximum technician hours available) also changes as a function of time. We have added another layer of filtering over the historic time series dataset where we chop off some data at the beginning (Beg Date) and ending (End Date) by evaluating the model accuracy metrics, as shown in Figure 4. This helps us remove time series data which may be outlier in terms of changes happening at the facility due to an unplanned facility shutdown or a high criticality maintenance event. Thus, filtering historic time series data filters out anomalies which may impact the robustness of the forecasting model.

4.3 2-stage SARIMAX based model

In stage 1, we create multiple S-ARIMAX models by varying the length of historic dataset and calculate their AIC values. The length of the historic dataset is varied by changing the beginning date (Beg Date) and end date (End Date), refer Figure 4. From this historic dataset, we select the training dataset using the hold out ratio 1. Next, we train the S-ARIMAX model using this training dataset. For training each S-ARIMAX model, we pick different parameters from a grid of (p, d, q)- (P, D, Q) values and pick the top 10 S-ARIMAX models with the lowest AIC values and statistically significant parameter estimates ($p < 0.05$), as shown in Table 2. For the top 10 models picked from Stage 1, we forecast values by breaking the time series actual data (historic data) into train and test using hold out ratio 2. Then, the forecast values for these 10 models are scanned again to check for forecast values which cross the maximum technician availability hours (max hrs) for the facility. If the forecast values exceed the maximum technician available hours (max hrs) for the facility, then it is scaled to max hrs. The number of times scaling is done is counted and recorded as scaling fraction. In parallel, we also calculate MAPE/RMSPE for the test data (out of sample values based on hold out ratio 2). Now, we have calculated 3 metrics viz. MAPE, RMSPE and count of smoothing/scaling for each of the 10 models for a given facility and time series combination (refer Fig.5). We identify the best model as the one which has the lowest MAPE

Table 1: Comparison of different Forecasting Techniques

Forecasting Techniques	Billable (b=p+r+t)	Admin (a)	Billable: Reactive (r)	Billable: Project (p)	Billable: Training (t)
Metric(X=US Holidays)	MAPE	MAPE	MAPE	MAPE	MAPE
Deep AR*	38.73	143.2	44.35 (p50)	71 (p10)	96 (p10)
TBATS	52.11	24.86	-	-	-
Holts winter	40.32	149.77	-	-	-
SES	39.25	115.36	-	-	-
SARIMAX**	37.71	24.5	15.22	30.5	241
ARIMAX	42.25	56.26	42.5	57.5	241
Median/Mean	56.8	-	65,55	76, 121	$>$ 1e3
Method of proportions	-	-	94	149	$>$ 1e7

Table 2: SARIMAX Model Parameters

Dep. Variable:	y	**No. Observations:**	44
Model:	SARIMAX(3, 1, 3)x(2, 1, [1, 2], 7)	**Log Likelihood**	-82.010
Date:	Mon, 22 Aug 2022	**AIC**	188.021
Time:	10:10:35	**BIC**	207.023
Sample:	0	**HQIC**	194.653
	- 44		
Covariance Type:	opg		

	std err	**z**	**P$>$ |z|**
holidays	1e-06	-7.73e+07	0.000
ar.L1	3.25e-11	-6.58e+09	0.000
ar.L2	5.31e-10	4e+08	0.000
ar.L3	2.02e-09	4.96e+08	0.000
ma.L1	2.75e-08	1.06e+08	0.000
ma.L2	9.47e-10	3.09e+09	0.000
ma.L3	9.48e-09	1.06e+08	0.000
ar.S.L7	6.42e-09	3.11e+08	0.000
ar.S.L14	1.9e-08	-5.25e+07	0.000
ma.S.L7	4.12e-09	4.85e+08	0.000
ma.S.L14	4.31e-10	2.32e+09	0.000
sigma2	5.03e-07	2.3e+09	0.000

Ljung-Box (L1) (Q):	6.47	**Jarque-Bera (JB):**	735.60
Prob(Q):	0.01	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.00	**Skew:**	3.70
Prob(H) (two-sided):	0.00	**Kurtosis:**	23.87

and has a count of smoothing/scaling fraction not exceeding 20 percent for the given time series and facility combination (5). The proposed approach varies multiple model hyper parameters (historic data selection window, hold out ratio for stage 1, SARIMA model order and hold out ratio for stage 2) to identify the best forecasting model based on MAPE/RMSPE as well as scaling fraction/count. All these hyperparameters are summarized in Table 3.

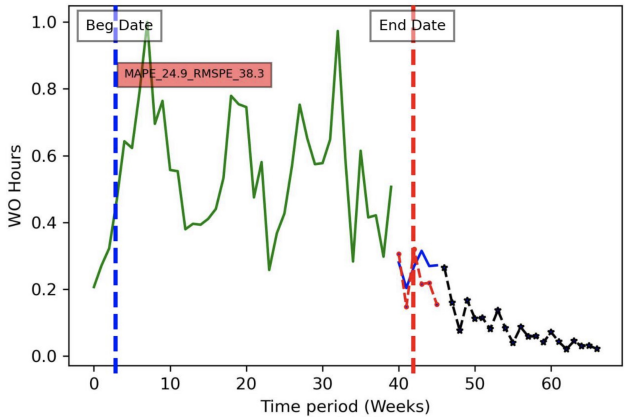

Figure 4: Window Hyper Parameter: Selection of Training Data

5 Deployment Infrastructure

Currently, AMFM model has a data pipe which fetches real time time series data of Workorder hours for each type. Next, this time series data is post-processed by the Forecasting model hosted in an EC2 instance, as shown in Figure 5). All modules of AMFM are written in Python and utilizes AWS infrastructure for data storage/handling (refer Figure 6). It's solver module uses the statsmodel library which is an open source library for regression and forecasting problems [31]. AMFM users can access/visualize the forecast values for each time series as well as the aggregate by accessing the AWS Quicksight dashboard where the results are published every week. On the output side, the Quicksight dashboard provides several metrics including the forecast accuracy and actual vs. forecast values week on week.

6 Results

6.1 Results: Forecasting Model in Production

The WO forecasting model has been taken into production with the data engineering and cloud compute infrastructure built using the AWS Services like S3 buckets, Redshift for data storage and EC2 for cloud compute. We have also setup a mechanism to monitor the forecasts going forward,

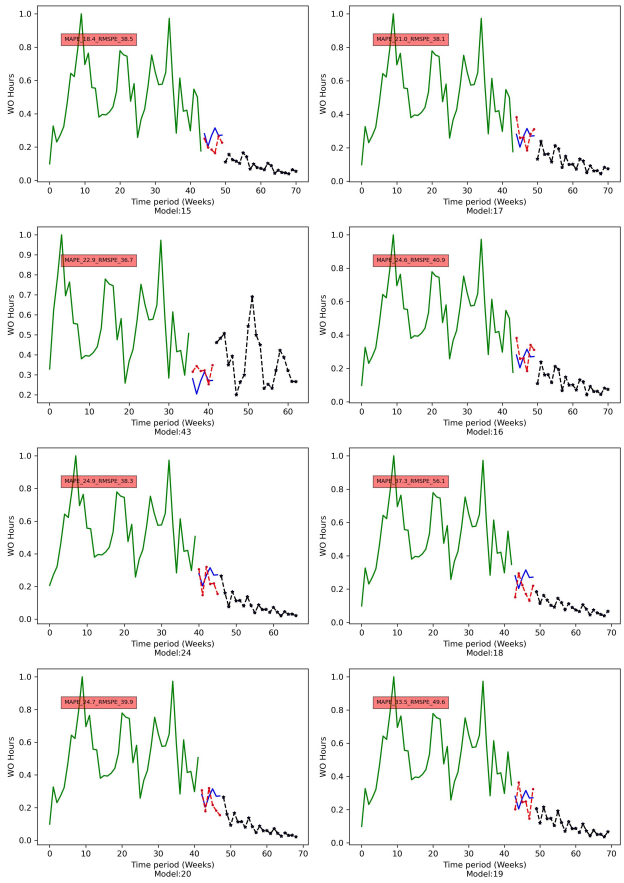

Figure 5: Multiple Forecasting Models developed using 2-Stage SARIMAX

using AWS Quicksight Dashboard. The forecast model runs once every week and publishes the forecast values to S3 buckets and Redshift tables. Currently, forecasts are made for all the facilities on-boarded and the forecast data is published to an AWS Quicksight Dashboard. In long run, a user interface would also be created around the forecast model which will be hosted in an auto scaling compute cluster with a code package for the end users to selectively run the model for their facility and consume forecast as flat .csv files.

6.2 Results: Accuracy Metrics

The proposed approach creates multiple models for each facility and then selects the best model in terms of MAPE, RMSPE and smoothing fraction. Table **??** and Table 4 summarize the accuracy metrics for the best model along with the model number. We can see that the accuracy metrics vary for different facilities as well as the SARIMAX model order. The accuracy statistics vary from one facility to another which in turn is dependent on the operating nature of each facility. This also highlights the importance of having

Table 3: Grid of Hyper Parameters: Forecasting Model Selection

Hyperparameter	Value 1	Value 2	Value 3	Value 4	Stages of optimization
p, d, q and s-P, D, Q	p-value<0.05, Stage1-AIC, Stage2-MAPE				Stage 1/2
Hold out ratio 2	0.7	0.8	0.85	0.9	Stage 2
Hold out ratio 1	0.7	0.8	0.85	0.9	Stage 1
Beg	365	355	345	335	Stage 1/2
End	0	5	10	15	Stage 1/2
Scaling count	15%				Post stage 1/2

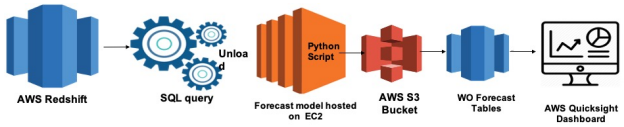

Figure 6: Forecast Model built and Deploy using AWS Stack

different models for each facility. Besides, the selection window specified in terms of Beg Date and End Date (refer Figure 4) which results in the best accuracy also varies from one facility to another. This demonstrates the importance of iteratively selecting the best historic time window for training to come out with the most robust forecast model. We carried out experiments by aggregating actuals of different WO types viz. p, t, r and used it to forecast billable workorder hours per week. The accuracy metrics viz. MAPE/RMSPE demonstrate lower values within acceptable limits as well more consistency, refer Table 4.

7 Conclusion

This paper developed a forecasting framework to predict required maintenance hours using a family of models customized for each facility and time series type. Development of the model involved understanding the workorder creation process of e-commerce facility maintenance teams besides experimenting with different forecasting techniques and then performing a comparative analysis. Some important facts about the AMFM model are as follows:

1. SARIMAX turned out to be the best model for these time series for mid and short term forecasting. The result of this approaches is also easily explainable, but for long term high accuracy prediction of WO hours, we need to gather more features/exogenous variables.

2. Forecast accuracy has been improved by including US holidays as an exogenous variable. On a similar line, the impact of including pre-peak (days before surge in customer demand) ramp up dates as another exogenous variable model accuracy can be further explored to investigate if it could help account for spikes in demand of WO hours

3. The 2-stage SARIMAX approach, particularly the selection of historic time series data using a sliding window, helps select the training data by filtering out anomalous data points which do not follow the trend

4. Classical forecasting techniques like SARIMA augmented by business specific realities can help create forecasting models customized for each facility in a network of e-commerce facilities even with limited historic time series data.

5. Facility specific periodic planning of maintenance engineering work can be made more accurate by deploying workorder forecasting models across e-commerce facilities.

In the future, we plan to do a careful outlier detection exercise to build more robust models which provide repeatable high accuracy forecasts rather than models biased by outliers. This is why MAPE can be a better indicator of a forecast model's accuracy compared to RMSPE.

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Table 4: Accuracy metrics for Billable (b) Workorders Forecast, b = p+r+t, Run Date=02/08/22

Order	Ses. order	RMSPE	MAPE	Beg Date	End Date	AIC	Model_no	Sm. frac.	Facility	Model count
(0, 1, 1)	(0, 1, 1, 7)	22.1	30.2	07/08/21	03/07/22	352.0	53	0.0	1	315
(0, 1, 0)	(0, 1, 0, 7)	8.5	6.9	16/09/21	03/07/22	324.7	348	0.0	2	349
(0, 1, 2)	(0, 1, 0, 7)	29.1	19.4	27/08/21	13/07/22	394.1	128	0.0	3	209
(0, 1, 1)	(2, 1, 3, 7)	72.0	14.4	07/08/21	03/07/22	435.0	43	0.0	4	150
(0, 1, 0)	(1, 1, 0, 7)	25.2	17.7	17/08/21	02/08/22	341.5	57	0.2	5	201

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