Pattern Discovery and Forecasting of Attrition using Timeseries Analysis

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Abstract — **Attrition is the term used to describe when employees leave a company either voluntarily or involuntarily, for any cause including retirement, termination, death, or resignation. When employees leave, they take with them priceless tacit knowledge. Though it is a reality for any industry, if the rate of attrition is very high, it creates enormous pressure on the process to function effectively. This is precisely what a leading organization's transportation Line of Business (LOB) is going through where attrition is hovering around 34% for the last three years. Time and again, it has struggled with managing a healthy attrition rate. As a result, there has been a constant occurrence of missed Service Level Agreements (SLAs) resulting in huge penalties.**

For managers, managing workload has become extremely tedious in the current context. With the constant change in the management team, the focus keeps shifting from one approach to another.

Keeping the above problem in mind, this study aims to forecast attrition using time series analysis at various levels based on only the attrition data available for the last fourteen months. The hypothesis here is, if probable attrition is forecasted well in advance, a plan can be put in place to hire employees and make them available whenever there is demand from contract managers. This in turn can help individual contract managers manage their workload efficiently, and reduce their missed SLAs, thereby reducing penalties.

The proposed solution is to compare various Time Series Forecasting techniques like Auto-Regressive Integrated Moving Average (ARIMA), Seasonal Auto-Regressive Integrated Moving Average (SARIMA), Exponential Smoothing (ES), Holt-Winters (HW), Moving Average, Ratio to Moving Average, based on attrition date of the last 12 months. The forecasted data is then compared with the following two months' attrition data to arrive at the best possible solution.

The novelty of this study is the use of time series forecasting techniques to forecast future attrition trends specifically based on attrition data, which has not been explored much. This forecasted data can be used to better workload management which in turn is expected to reduce missed SLAs and penalties.

Keywords: Forecasting, Timeseries, ARIMA, Seasonal ARIMA, Exponential Smoothing, Holt-Winters, Data Discovery, Pareto, Trend Analysis, Regression, Moving Average, LSTM

I. Introduction

For any organization, finding the right candidate is of paramount importance. However, this is just the first step. Then there starts a long journey of fitting the candidate into the right job. This is not only time intensive, but also involves a huge cost of orientation and training [1]. However, when the same candidate decides to leave the organization within a year, it creates a huge void jeopardizing the entire setup with a cascading effect going down till contract termination.

That is the condition the transportation LOB is going through. With attrition going up the roof, the transportation LOB is struggling to meet its SLAs resulting in a huge outflow of money in form of penalties.

The hypothesis here is that if probable attrition is forecasted well in advance at various levels, a plan can be put in place to hire employees and make them available whenever there is demand from contract managers.

In recent times, human resource departments of various organizations have been trying to map the employee life cycle which involves a lot of phases [2]. Using machine learning algorithms, predictions are being made about employee tenure within organizations [3]. However, when there is a lack of good Human Resource (HR) data, the scope becomes limited.

The study aims to find an easy-to-use attrition forecast solution which in turn could help individual contract managers manage their workload efficiently, and reduce their missed SLAs, thereby reducing penalties.

To have a better understanding of the attrition problem and various time series techniques, a detailed literature review has been conducted as discussed in the next section.

II. Literature Review

Employee attrition is a very costly affair for any industry. The direct costs of workforce turnover include the cost of hiring new employees, the cost of training new employees, the time it takes to transition, the cost of temporary employees, the cost of lost expertise, and the cost of the job itself [4].

Several studies have been conducted on employee attritions. However, most of the employee attrition studies have concentrated on using various Machine Learning Algorithms using several factors. In the study [5], several machine learning algorithms like Decision Tree, Support Vector Machine (SVM), Random Forests have been used to estimate if an employee will leave or not.

In another study [6], Gaussian Naïve Bayes classifier has been used to classify if an employee will attrit or not. XGBoost classifier has also been used to classify employee attrition [7].

As seen in most of the studies related to attrition predictions, classification is the most used approach. However, using time series techniques to forecast future attrition has not been explored enough based on the observations during the literature review. This establishes a unique opportunity for this study.

Generating scientific projections based on data with historical time stamps is known as time series forecasting. It entails creating models through historical study, using them to draw conclusions and guide strategic decision-making in the future [8].

Timeseries analysis and forecasting are important for a variety of applications, including business, the stock market and exchange, the weather, electricity demand, cost, and usages of goods like fuels and electricity, etc., and in any setting where there are periodic, seasonal variations [9].

There are several time series techniques available, notably Moving Average, Exponential Smoothing, Holt-Winters Smoothing method, ARIMA, Seasonal ARIMA, LSTM, etc.

One well-known technical indicator, the moving average, is employed in time series analysis to forecast future data. Researchers have produced numerous variations and implementations of it during its evolution [10]. Another variation of the moving average is the Ratio to Moving Average, which is superior to the simple average method and is predicated on the idea that seasonal variance for any given month is a continuous component of the trend. Moving average methods reduce periodic movements if any [11].

Another immensely popular time series technique is Exponential Smoothing. Its popularity is based on the fact that surprisingly accurate forecasts can be obtained with minimal effort. This has been proved in this study as well where time series forecasting methods are used via an Excel (FORECAST.ETS) function. The superior efficacy of this model has been nicely illustrated in the paper by Dewi Rahardja. With this Excel function, forecasting is simple and quick while considering the model's level (intercept), trend (slope), and seasonality [12].

Another variation of the Exponential Smoothing technique popularly known as Holt-Winters after the name of the inventors is very effective when there is both trend and seasonality in the data. The two primary HW models are multiplicative for time series exhibiting multiplicative seasonality and additive for time series exhibiting additive seasonality [13].

However, there are times when, for the same number of data, a Long Short-Term Memory (LSTM) multivariate machine learning model outperforms a Holt-Winters univariate statistical model [14]. By utilizing the nonlinearities of a particular dataset, LSTM networks can overcome the constraints of conventional time series forecasting methods and produce state-of-the-art outcomes on temporal data [15].

From a statistical modeling perspective, another time series technique that produces a robust result in short-term prediction is ARIMA, first introduced by Box and Jenkins in 1970. It consists of a series of steps for locating, calculating, and diagnosing ARIMA models using time series data. A very well-researched paper available in this context is [16], which shows ARIMA's strength in predicting future stock prices. The limitation of ARIMA model is however the number of periods. It is recommended to employ at least 50 and ideally 100 observations [17].

While ARIMA has its own strength, when it comes to seasonal data, there is a variation of ARIMA available commonly known as SARIMA or seasonal ARIMA. For climate-related data, SARIMA has been a valuable tool [18].

With a lot of statistical techniques already being widely used in forecasting techniques, recent studies have now been conducted using Deep Learning (DL) models showing outstanding results when compared to traditional forecasting techniques. A comparative study [19] has shown that the DL method significantly improves upon Machine Learning (ML) models.

III. Problem Statement

It has been observed that, in the last 14 months, close to $2,082k has been paid in terms of penalties in transportation LOB. Penalties are incurred when SLAs are not being met.

One of the main reasons identified is "attrition" which presently stands at 34%. This has almost remained constant for the last three years.

With constant churn at top management and lack of HR support, there seems almost no headway in managing attritions. Ironically, the lack of HR support is due to the fact that HR department has failed to manage its own attrition rate.

The problem is further exacerbated due to the lack of proper data collection at the HR end. With the limited data and considering the present problem area, this study aims to do the following:

1. Identify the required attrition dataset. In this case, only the attrition data for the last 14 months are available.

2. Study data at various levels and categories to identify trends, patterns, and top contributors which then will be used to create subsets of the main dataset for modeling.

3. Explore various time series techniques to identify the best time series forecasting model which can be used to forecast future attrition.

IV. Methodology

This study uses Cross-Industry Standard Process for Data Mining (CRSIP-DM) framework which is discussed below.

The first phase is to understand the business in context. For this study, the transportation LOB is considered which is reeling under huge attrition for the last 3 years.

The next phase in CRISP-DM process is data understanding. Here, the data is the employee attrition record captured for the last 14 months. The other data points are missed SLA numbers at contract levels and penalties paid at contract levels for the last 14 months.

The third phase involves data preparation. The goal here is to identify if the data is fit for time series analysis. This involves looking at trends to see if there are any strong upward or downward trends. Along with this, the data is further analysed for any seasonal trends. Based on the findings, data transformation can be done to make the data stationary.

The main approach in the modeling phase is to select the best time series forecasting technique like Moving Average, ARIMA, SARIMA, Exponential Smoothing, and Holt Winters.

Post modeling technique, the evaluation phase starts. In this phase, the efficacy of the various time series forecasting techniques is assessed. The one which most accurately mimics the test data would be finalized.

In the deployment phase, the forecasted numbers can be used to hire a pool of employees. These employees will then be suitably placed in various contracts based on the current need.

A. Business Understanding

The transportation LOB is one of the most profitable units in this organization. It provides the following solutions as depicted in TABLE 1 to its client.

TABLE 1. Transportation Solutions

Solutions	Description
Automated Tolling	Captures vehicle details when a tolling both is crossed and bills customer accordingly. A team also works on dispute resolutions pertaining to technical failure, failed auto-debit attempts, customer complaints, etc.
Automated Parking	It provided intelligent parking solutions mainly for governments. The solution involves fee collections, dynamic pricing, enforcement solutions, etc.
Public Safety	It provides automated photo enforcement, traffic violation solutions, etc.

However, the biggest challenge is the abnormal attrition rate for the last 3 years which on average is around 34 %. Managers are finding it difficult to manage their workload efficiently.

Apart from providing technological solutions, there are dedicated teams working on resolving disputes pertaining to technological failures, missed billing, payment disputes, failed payments, etc. There are agreed Turnaround Time (TAT) for resolving disputes which are part of SLAs with individual contracts.

There are also several SLAs linked to penalties. A missed SLA incurs penalties to be paid to the client. It has been observed that almost $ 2,082k penalties is paid in the last 14 months by the accounts reeling under huge attritions.

Since dispute resolution is manually intensive work, more employees are needed during peak times. But with a lack of available manpower due to high attrition, dispute resolutions often lead to missed TAT, and missed TAT leads to penalties being levied at contract levels.

This study aims to forecast probable attrition, which can help plan workload management efficiently thereby can help control missed SLAs and bring down penalties to an acceptable level.

B. Data Understanding

The attrition data collected for this study contains some important parameters as described below.

1. Employee details – ID, Employee Name, Salary, Last Performance Rating
2. Employment Details - Employee Type (Regular or Contract), Joining Date, Termination Date, Employee Level, Type of Termination, Termination Code, Cost Centre, Job Name
3. Contract Details – Contract Name, Sector, Business Category, Location City, Country

For this analysis, the focus is on the contract level. The following plot as appears in Fig. 1 shows a Pareto Chart of Attrition vs Contracts. It clearly shows top 6 which represents 15% of overall contracts are contributing to more than 80% of attrition.

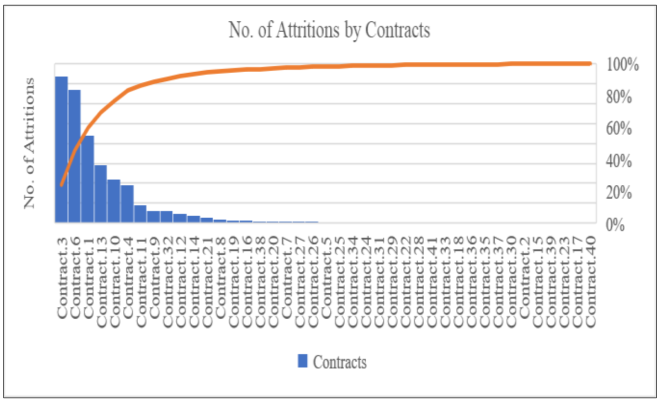

Fig. 1. Pareto – No. of Attrition by Contracts

It is also observed that the penalties paid by the top 6 contracts which total to $1,051k representing ~50% of overall penalties.

There is also a strong correlation of 0.93 exists between contract level attrition numbers and missed SLAs. Fig. 2 shows a scatter plot relation between attrition numbers and missed SLAs at contract levels.

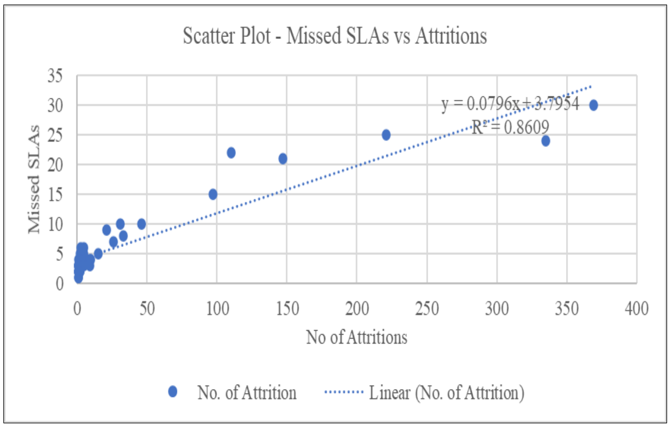

Fig. 2. Scatter Plot - Missed SLAs vs Attrition

An almost similar strong correlation is detected between missed SLAs and penalties paid at contract levels as shown in Fig. 3.

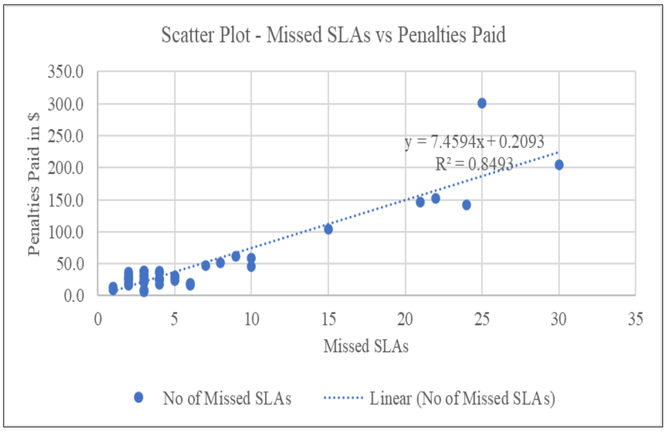

Fig. 3. Scatter Plot - Missed SLAs vs Penalties

Another key point that came out prominently is that close to 90% of attrition is at the junior most level (C01). Fig. 4 highlights this fact.

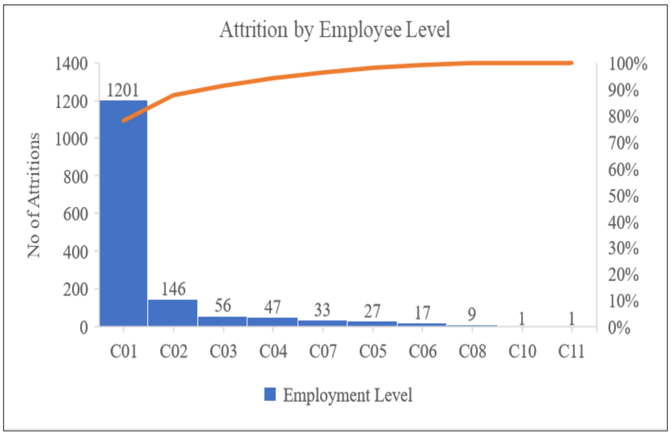

Fig. 4. Pareto Graph - Attrition contribution by Employee Level

This finding remains consistent with the overall contract level attrition trend.

A few other levels that are considered for this study are location-wise attrition and salary range. At various locations, Fig. 5 shows that the top 11 cities contributed to 80% of attritions in the last 14 months.

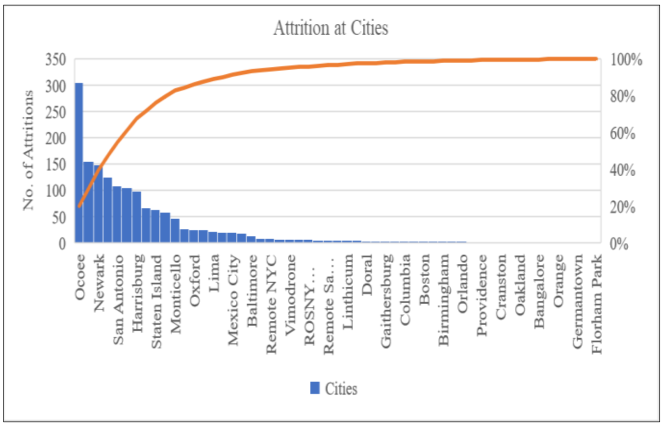

Fig. 5. Pareto Graph - Attrition contribution by cities

Attrition at the pay level is the last set of data that is examined. The salary bucket is created to identify a certain range causing attrition. The salary range of \$20k to \$40k is the one that causes the most attrition as shown in Fig. 6.

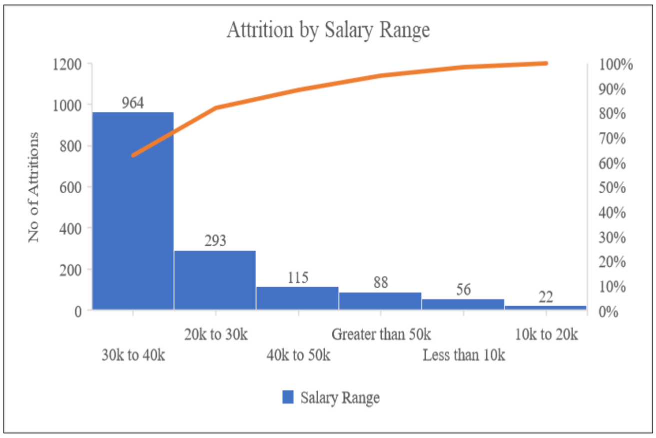

Fig. 6. Pareto Graph - Attrition contribution by salary bucket

C. Data Preparation

Based on termination date, the attrition data is divided into five qusrters with each quarters consist of three months of data. The first 12 months of data have been used for modeling and the last 2 months of data have been used for testing forecast accuracy.

Again, based on the termination date, the month with "MMM-YY" format is created. The quarter and the month form the basis of forecasting data.

The salary bucket is created to understand if there is any particular salary range that is contributing to high attrition. The buckets created here are "Less than 10k", "10k to 20k","20k to 30k", "30k to 40k", "40k to 50k" and "Greater than 50k".

To summarize, the data is divided into the following six categories for forecasting purpose. This was done in order to account for every level that could significantly affect the forecasting outcomes.

1. Overall attrition by quarter and month-wise.
2. Attrition by top contracts, quarter and month-wise.
3. Attrition by top employment levels, quarter and month-wise.
4. Attrition by top contracts and top employment level, quarter and month-wise.
5. Attrition by top cities, quarter and month-wise.
6. Attrition by top salary ranges, quarter, and month-wise.

The above categorizations form the basis of the forecast modeling.

D. Modeling

Considering the limitation of the available information in the dataset, various time series forecasting techniques are considered on each of the categorized levels of data and compared. The top technique is chosen to predict future attrition. The forecasted attrition result is further used as the input of regression to predict missed SLAs numbers and the predicted missed SLAs to predict probable penalties. These approaches are discussed in detail in the following sections.

The modeling approach starts by taking the overall data and by checking for stationarity of the data using Dickey-Fuller (DF) test. The low p-value of 0.0395 observed during DF test which is less than 0.05 indicates that the data has no unit root and is stationary. This result remains consistent for all other 5 datasets.

Then a quick check on the trend graph shows an overall upward trend as appears in the Fig. 7. This is a bit contradictory to the findings in Dickey-Fuller test. However, this trend is observed for the other 5 subsets of the data.

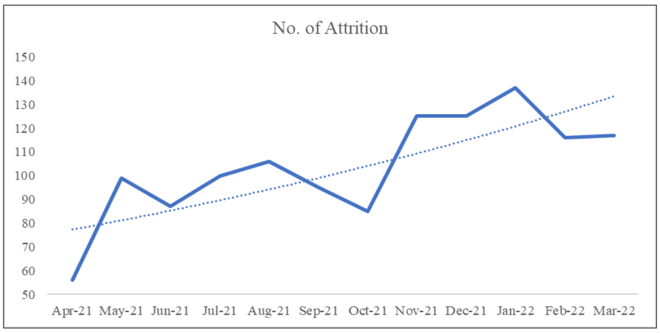

Fig. 7. Attrition trend

The first technique used is Moving Average (MA), which is followed by ratio-to-moving-average and Exponential Triple Smoothing (ETS) using Microsoft Excel's FORECAST.ETS formula.

In the MA, the moving average of three months is considered. This is done since the months are divided into quarters with each quarter consisting of three months.

Building on MA, the next technique that is used in ratio-to-moving-average. This contains some additional steps like deseasonalizing the data and building a regression model on the deseasonalized data to forecast. This method is frequently used to show the data's overall movement without taking seasonal effects into account.

The next forecasting technique considered is Microsoft Excel's in-built forecast algorithm. It uses FORECAST.ETS function and allows for auto-detection of seasonality. The other in-built function FORECAST.ETS. STAT is used to show some important stats related to FORECAST.ETS predictions.

The ARIMA, Holt-Winters (Smoothing 1, Smoothing 2 Additive & Multiplicative, Smoothing 3 Additive and Multiplicative), and LSTM techniques are also explored using python. For ARIMA, the auto ARIMA is used to find the best combination of the order (p,d,q). The best order found is (1,0,0). This order is used in ARIMA Model to forecast attrition.

Since ARIMA could not perform as expected, it led to another technique called LSTM. It is a kind of recurrent neural network that can pick up order dependence in situations involving sequence prediction. The data is divided into train and test data. After selecting test and train data, "MinMax" preprocessing technique is used on both datasets. The LSTM technique has also performed on the given dataset as expected and hence the technique is dropped for consideration on other datasets.

Finally, Holt-Winters smoothing technique is used to see if the forecast can be improved. It uses a modified version of exponential smoothing to account for a linear trend. Simple smoothing is used where the result observed is poor.

The Holt-Winter Exponential Double Smoothing is then tried to see if the forecast can be improved further. Though, the results improved but not as expected.

The last Holt-Winter Exponential Smoothing technique used is Triple Smoothing to see if the forecast can be further improved upon Excel's FORECAST.ETS function.

Finally, the forecasted attrition data is used to create a regression model to predict the missed SLAs as shown in Equation (1). The predicted missed SLAs then become the input to Equation (2) to predict penalties.

$$\text{Predicted Missed SLAs} = (0.07958 * \text{Forecasted Attrition}) + 3.7954 \quad (1)$$

$$\text{Predicted Penalties} = (7.45942 * \text{Predicted Missed SLAs}) + 0.20933 \quad (2)$$

E. *Model Evaluation*

Once all the forecast techniques are used, a summary showing the model performance is presented in TABLE 2.

TABLE 2. Model Performance on overall attrition data

TS Models	MAD	RMSE	MAPE
Moving Average (3)	9.6	10.9	9%
Ratio-to-Moving-Average	11.0	12.9	12%
ETS	13.2	14.0	10%
ARIMA	15.8	18.7	14%
Holt Winters ES1	27.5	30.5	25%
Holt Winters ES2_ADD	12.1	13.5	13%
Holt Winters ES2_MUL	18.9	25.0	18%
Holt Winters ES3_ADD	16.9	19.1	16%
Holt Winters ES3_MUL	21.3	24.3	20%

When overall attrition data is considered, the best forecast technique is the Moving Average for which the MAPE is 9 %.

The graph in Fig. 8 shows how well the forecasted values perform against the original values.

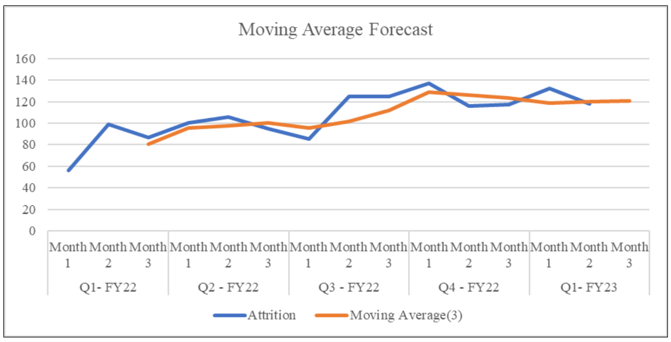

Fig. 8. Moving Average performance on overall attrition

The same approach is used for the other datasets to check if there is any significant difference between the various time series technique used.

V. Analysis and Results

The forecasting techniques are tested on the actual attrition data of the following two months (Month 1 and Month 2). When the overall data is used, the Moving Average model is giving MAPE as 17% shown in TABLE 3 compared with the result received at the time of modeling which is 9%.

TABLE 3. Moving Average Model Outcome for Overall dataset

Overall Data					
Month	**Attrition - Actual**	**MA (Forecast)**	**MAD**	**RMSE**	**MAPE**
Month 1	132	118.8	**25.8**	**28.6**	**17%**
Month 2	158	119.7			
Month 3		120.6			

Since there is a difference of 8% between the actual versus the model prediction, the ETS is used to compare the results with the Moving Average. The ETS shows better performance on the actual numbers as shown in TABLE 4.

TABLE 4. ETS Model Outcome for Overall dataset

Overall Data					
Month	**Attrition - Actual**	**ETS (Forecast)**	**MAD**	**RMSE**	**MAPE**
Month 1	132	128.7	**14.0**	**17.5**	**9%**
Month 2	158	133.4			
Month 3		138.2			

For top contracts, both Moving Average and ETS can be used as their results are almost similar with MAPE for ETS is 6% whereas for Moving Average it is 5%. The results are shown in TABLE 5 and TABLE 6 respectively.

TABLE 5. Moving Average (MA) Model Outcome for Top 6 Contracts

Top 6 Contracts					
Month	**Attrition - Actual**	**MA (Forecast)**	**MAD**	**RMSE**	**MAPE**
Month 1	116	103.8	**6.3**	**8.6**	**5%**
Month 2	126	125.6			
Month 3		111.4			

TABLE 6. ETS Model Outcome for Top 6 Contracts

Top 6 Contracts					
Month	**Attrition - Actual**	**ETS (Forecast)**	**MAD**	**RMSE**	**MAPE**
Month 1	116	111.9	**7.1**	**7.6**	**6%**
Month 2	126	116.0			
Month 3		120.2			

For the rest of the datasets, the ETS model result is considered since it gives the best and most consistent results across all datasets.

Finally, using the regression Equation (1) and Equation (2), predicted missed SLAs and penalties on overall attrition data are calculated respectively as shown in TABLE 7. The same concept can be used for all other 5 datasets.

TABLE 7. Predicted Missed SLAs and Penalties

Overall Data			
Month	**ETS (Forecast)**	**Predicted Missed SLAs**	**Predicted Penalties in ($ k)**
Month 1	128.7	14	104.9
Month 2	133.4	14	107.7
Month 3	138.2	15	110.6
Total		**43**	**323.2**

VI. Conclusions and Recommendations for Future Work

Attrition remains a burning problem in any sector, and it can have profound consequences when it is way above a tolerable limit.

Numerous research have been done to address this issue, however, when there is little information available, a simple solution can sometimes work wonders.

As seen here, the time series forecasting technique is used to predict future attritions across several datasets. Since this is a novel method for predicting attrition, multiple forecasting approaches are applied to a variety of datasets to determine the effectiveness of this method.

This study has shown that future attrition can be forecasted accurately even when only attrition statistics are available. The main forecasting method for all datasets has been FORECAST.ETS, a built-in Excel function.

To conclude, sometimes a seemingly tough problem can be tackled through simple approaches, in this case, attrition forecasting using time series techniques. This will help plan future workload effectively, and reduce missed SLAs and penalties.

However, this approach is suitable only when the data dimension is less. In an ideal scenario, there can be several factors that may affect a company's attrition, but with limited data, this approach is a way out as it uses monthly attrition data to forecast probable attritions for the next 3 months.

Just like with any other data modelling technique, this work has to be replicated on new datasets to determine its validity. More the data, the better the result expected as it may throw up additional trends which are probably missing in the current context.

Due to the novelty of this strategy in the current AI / ML era, the approach used in this study would open the door for similar studies in attrition predictions.

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