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# Automated System for forecasting and capacity management in BPO

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## Abstract

In the virtual world, every decision made by executives today need forecasting. Sound forecasting of demand and variations are no longer an extravagance but a necessity, since Operations in the organizations have to deal with the seasonality, sudden changes in capacity management, cost-cutting strategies of the competition, and enormous dynamics of the economy.

This paper details the development of a Forecasting and Capacity Planning model to empower operations to consistently forecast incoming volume for scheduling/rostering. A combination of past process-specific data, algorithmic forecasting, Subject Matter Expert (SME) inputs, and modelling results in a forecast with a daily accuracy of up to 85% per month out and approximately 95%-98% per week. The tool leverages the generated forecast to envisage capacity and resource planning. This Capacity Planning tool gives the capacity requirement for the forecasted volume, scheduling, and staffing. The tool has been deployed across 150+ client area. POC (Proof of Concepts) was done across all domains to test the tool and as expected the tools is generating the forecast and schedule with the accuracy of 96.77%.

**Keywords:** Data models, capacity modelling, extrapolation, knowledge models, prediction intervals, predictive validity, regression analysis, time series data

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## 1. Introduction

Capacity planning [1] refers to the process of translating number of resources required to meet the demand to process the transactions. This real-time study is about the challenges faced by the delivery units in a BPO i.e., Business Process Outsourcing. Delivery units or the operations' who struggles to meet client requirements in absence of automated system to manage the capacity requirement. They miss the Service Level Agreements (SLAs) as they are not able to manage inflow volume of the transactions. Despite of all technological advancement and automation, there is a lack of ability to gauge accurate volume inflow. There is a considerable variation in processes today due to seasonality /cyclical components present in the process, in absence of accurate volumetric details received from the clients. This has led to inaccurate capacity estimation causing longer cycle time/breach in SLAs and eventually in client dissatisfaction. This is the common issue observed in all delivery units across all the domains like Finance and accounting, Resources, Utilities, Insurance, and Healthcare.

As a result, operations are being capacitated to the best efforts to meet the client requirement, leading to inefficient resource management impacting Operating Deals Economic (ODE) directly and leading to revenue leakage. These further impacts client satisfaction. The current methods need to be tweaked to accommodate the volume spikes. This is largely depending on the gut feeling of the managers. This results in multiple forecasts across the processes. These multiple forecasts without any baselining lead to misalignment with the forecast at the organizational level.

Owing to the ongoing issues, the need of the hour is to create an end-to-end system, which not only forecasts but can

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also estimate the best fit capacity for the operations and create a visual dashboard for Eye on Glass analysis and send early warnings to mitigate the risk. The system should act as a whistleblower and proactively send alerts to the operations team so that they can manage the resource alignment basis the current forecast generated by the system.

The objective of the study is to develop an end-to-end Forecasting and Capacity Management tool which gives more accurate volume forecasting leading to efficient capacity management. The tool proposed to generate forecast based on the quantitative analysis on the historic data captured. This subsequently will improve Operating Deal Economics (ODE) and eventually help in reducing client noise caused due to capacity misalignment.

## 2. Materials and Methodology

### 2.1. Literature Reviewed

For this study, various reports and articles have been referred in the area of forecasting and capacity planning.
**Forecasting Methods -**As seen historically, organizations have included some extent of forecasting methodologies in their systems [2] [3] [4]. There have been many technological advances in the forecasting techniques since years, however, most of the systems/tools still generate very basic level of forecast. The actual advantage of forecasting is when it is used over several time interval/ frequencies (daily, weekly, quarterly, annual and real-time basis) and is combined with daily operational workflow, and planning is fully merged with Process Improvement (PI) initiatives. There are five main forecasting methods that jointly enable these benefits in a Business Operations:

- **Predictive Modeling:** This method [5] uses historic data to determine instances that might results in some unexpected events to happen.
- **Algorithmic Modeling:** In this method, averages and distributions of historic data are combined in an algorithm to generate a forecast.
- **Pattern Identification.** Trend analysis is an important ingredient in building up of basic forecasts. Identifying trends and patterns in historical data is one of the commonly used methods for forecasting.
- **Scenario Modeling:** Once a baselining is done it should be validated by the operations for the expected changes that can influence the forecast.
- **Preventive Visual Management (Dashboard):** A simulation is developed to model and assess the impact of multiple scenarios and a rea time dashboard is generated.”

Capacity planning [1] refers to the process of translating number of resources required to meet SLAs. Some broad categories that fall under capacity planning are:

- Recruiting staff to fulfil the forecasted demand. Scheduling is an important part of operations. The increasing issue owing to scheduling has led development of more complex models. The objective is to identify issue at broad level, compare different methods and identify the best method suited [6] [7].
- Having enough resources for the volume in hand. It was important to study people management at work [8] [9].
- Ensuring everything needed to complete targets

To summarise, capacity planning is all about preparing for the future in the best possible ways, create better operations design, and even identifying tailbacks in the supply chain prior to the occurrence [10]. The journal referred here addresses optimisation model applied for tactical capacity planning [11] [12].
**Capacity Model:** To do the Capacity Planning the requirements were:

- **Initiate demand forecast**- Brainstorming on the requirements to meet the upcoming volume (fulfilled by the Forecasting tool).
- **Determine the required capacity.** From the forecasted volume estimate required headcount.
- **Calculate headcount requirement**- Determine current headcount for the concerned duration
- **Measure the gap**. Determine the variation between forecast and resource capacity.
- **Map capacity with the demand**- If current headcount is more than demand, there is a fair chance of team taking up additional work, complete target before TAT in long terms leading to reduction in headcount. If the demand is greater than the capacity, then there is a need to scale up the team [13].

For this tool Erlang C model was used to determine the capacity. This model was used since it helps establishing relationship between scheduling & volume and response time. This clearly gives the resources required for the forecasted volume.

Erlang C was formulated by Danish mathematician Agner Erlang in 1917. The Erlang C formula is used to calculate the headcount required, to process given volume to achieve SLA targets [14]. This gave real-time staffing data.

This gives volume on hourly basis. Here are various Erlang Models that are commonly used:

- **Erlang B –** This is the most commonly used model which gives the number of agents required at the peak hour
- **Extended Erlang B-** This model takes into account that a percentage of calls are immediately repeated if they encounter blocking (a busy signal).
- **Erlang C-** This model can be applied in the BPO domain for scheduling & staffing.

## 2.2 Methodology

Various methodology/framework were evaluated in the planning phase. Basis the industry experience, working guidelines were formulated to develop the working model. TDSP and CRISP were two methodologies that were zeroed in. Since TDSP required specific specialized skill set, CRISP-DM methodology was referred to approach the solution. The CRoss Industry Standard Process for Data Mining (CRISP-DM) serves as the base model for a data science process. This methodology has basically six stages/steps [15]:

- Due Diligence – This section deals with business requirements?
- Data understanding – What kind of data is required? Is it present in the system. Cleansed data?
- Data preparation/design – Data structure and organisation?
- Modelling – Decide on appropriate modelling technique that can be utilised
- Evaluate – Evaluate and decide which model can be used that suits business requirements
- Implementation stage – Implement the model

There are four approaches considered for forecasting:

- Using a tool that utilises advanced forecasting methodology assisted with data-gathering, data exploration, best case scenarios and advanced machine learning techniques.
- Using a simple and methodical approach.
- Using a random approach based on human judgement.
- A combination of above-mentioned approach

There are total of 500+ accounts in the organization, as a current scope, Finance and accounting processes were chosen for the tool deployement. Within Finance and Accounting, the tool was deployed in Invoicing process from Procure to Pay area. Once the model is succeessful deployed in Finance and accounting area, tool was planned to be replicated in other domains like healthcare, utilities, banking and finance etc.

The incoming volume is captured in the forecasting model, which generates a forecast based on the algorithm. The forecasted volume is pushed to the capacity planning tool, which accordingly generates the scheduling and staffing requirements, as shown in Fig. 1.

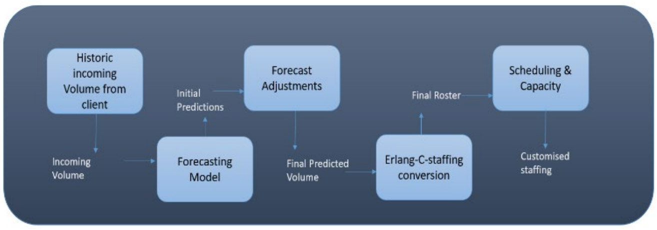



**Figure. 1.** End-to-end architecture

## 3. Data Understanding and Preparation

Each process is unique in the organization, and it is tedious task to identify all relevant variables to determine the method of measuring them and get those variables into the data warehouse. Data measurement differs in all kinds of processes. The most challenging part of establishing a successful modelling program is to determine a common method to measure the data and get the entire data collated in the data warehouse. The relevant point here is to maintain the data warehouse over a period of time. This needs to be revisited at a pre-decided frequency interval. To ascertain the accuracy of the models that are being built, they must be calibrated and reweighted at regular intervals.

The data collection stage involves identifying the type of data that is required and what is readily available within the process. Additionally, many patterns are observed in the available data sets due to seasonality, and it is important to identify the patterns to select the most suitable forecasting model. In a process like an Invoice processing, the data flow is regular throughout the month however shows a spike at the month end and the start of the month. However, in the Accounts Payable process, the volume spike is at the month's end when buffer staff is required to fulfil the requirement, whereas they have idle time throughout the month. Here there is a visible variation in the processes, and there is a dire requirement to create and deploy scientific methods to have valuable insights into the data and forecasting.

The data collection plan was laid down to collect the data and further cleanse it to be captured in the data warehouse. Since the nature of the processes is majorly transaction based with daily or weekly frequency data. So, the approach is to try different combinations of models, using techniques like the exponential smoothing model, Holt Winter's classification models, time series decomposition model, etc., and then pick the best fit model. For the study, time series data is with at least 30 data points (transactions) is used, to develop and test the models to forecast the volume (transactions).

As a best practice, the models must be calibrated and reweighted consistently at a defined frequency interval. In the current scenario, the model is required to be calibrated at least every 2 to 3 months [16].

## 3.1 Data Collection and Understanding

- Design the data collection warehouse to support the modelling.
- Collect the data based on the data collection plan designed as a part of the research work
- Data cleansing is required to cleanse the past data and capture it into the newly designed data warehouse
- Data capturing and cleansing on a continuous basis.

Cleansed, specific, and accurate data is mandatory for successful modelling. The data should be process specific not the company as a whole. Limited data is provided by the operations team for the study to develop the required model.

To test the accuracy of the model, at least 30 data points (transactions) are required from the past data.

***Note: Only inflow volume is required to be considered to run the model and not the processed volume.***

The forecasted volume then feed to the capacity model to generate the staffing schedules, dashboards, Management reports, and finally early alert system.

## 4. Modelling

The forecasting tool should not rely on any assumptions or knowledge of the data's characteristics. Different combination of models and techniques were tried and tested, like Pegel's classification and Holt Winter's classification models to pick the winners.

The outcome of the analysis shows how the different methods of obtaining initial values can affect the accuracy of the forecast generated. Post parameter optimization, the differences are reduced to minimal [17]. The framework is depicted in the diagram as shown in Fig. 2.

can use Holt's linear trend method for forecasting. Holt method extends a simple exponential smoothing to permit the forecasting of knowledge with a trend. It is nothing quite exponential smoothing applied to both levels (the average value within the series) and trends [18].

Owing to the seasonality feature of the data, Holt Winter's method is the best option to choose from the types of Models available. This method comprises the forecast equation and three smoothing equations; one for the extent $L_t$, one for trend $b_t$ and one for the seasonal component $S_t$, with smoothing parameters α, β and γ.

- **Level** $L_t = \alpha (y_t - S_{t-s}) + (1 - \alpha) (L_{t-1} + b_{t-1})$;
- **Trend** $b_t = \beta (L_t - L_{t-1}) + (1- \beta) b_{t-1}$,
- **Seasonal** $S_t = \gamma (y_t - L_t) + (1 - \gamma) S_{t-s}$
- **Forecast** $F_{t+k} = L_t + kb_t + S_{t+k-s}$

The equation shows a weighted average between the seasonally adjusted observation and non-shows between the existing seasonal index, and seasonal index for the past years i.e., "s" time periods ago [19].

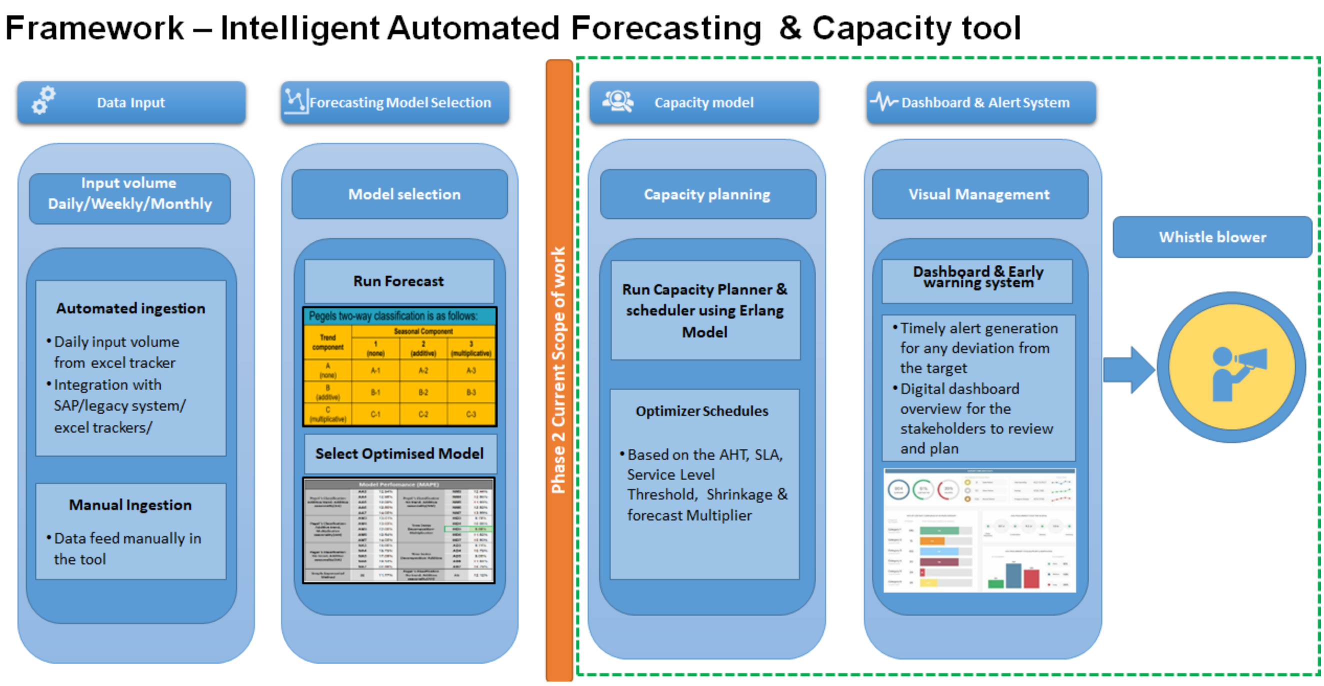



**Fig. 2.** Framework End-to-End Forecasting and Capacity Model

## 5. Forecasting Model

A method is required that can align the variation with the trend accurately in such a way that considers the trend of the dataset like Holt's Linear Trend method. The Time series dataset has three components which are Seasonality, Trend, and Residual. The dataset where visible trend can be observed

### 5.1 Capacity Model

Capacity Management can be defined as the process of

determining the required headcount for a process to meet forecasted volume. The *Erlang* C formula is a mathematical equation for calculating the headcount required to process a given volume to achieve SLA targets. This gives volume on an hourly basis. This model is used since it helps establish a

relationship between scheduling, volume, and response time. This provides the resources required for the forecasted volume.
Here are the observations:

- The measured errors are highly correlated positively across performance measures.
- The *Erlang C* model is on an average pessimistically biased but may become positively biased in case of high utilization and uncertain incoming volume
- The *Erlang C* model gives more accurate result when number of agents are significant, and utilization is low.

## 6. Model Evaluation

Once the tool is developed and data run on the tool, additive and multiplicative methods are found most appropriate to be used in the tool. The pictorial representation of the model output is shown in Fig. 3.

It is observed throughout the data analysis phase how the selection of one approach for obtaining initial values would affect forecast accuracy. After optimizing the values of the parameters, the differences can be minimized and clearly shows their effect on accuracy.

In the model, the required data points i.e., transaction numbers, are entered, and the model is run. Post the model run, Mean Absolute Percentage Error (MAPE) score was generated for all types of models that are used on the tool. MAPE score was evaluated as a response variable with different initialization methods of smoothing equations to impact the response variable. The results show the impact of the methods in obtaining initial values which is greater with multiple season Holt Winter's models with an additive trend.

## 7. Analysis and Results

In the tool, data is captured with a minimum 30 data points per transaction and the model is run. The tool generates a MAPE score, and the user can pick up the model from the MAPE score. The model with the lowest MAPE score is used to forecast volume, and the output of this is pushed into the

**Model Perfomance (MAPE)**

| | | | | | |
|---|---|---|---|---|---|
| Pegel 's Classification Additive trend, Additive seasonality(AA) | AA3 | 12.94% | Pegel 's Classification No trend, Additive seasonality(NM) | NM3 | 12.44% |
| | AA4 | 12.98% | | NM4 | 12.86% |
| | AA5 | 12.00% | | NM5 | 11.93% |
| | AA6 | 12.80% | | NM6 | 12.82% |
| | AA7 | 14.05% | | NM7 | 13.99% |
| Pegel 's Classification Additive trend, Multiplicative seasonality(AM) | AM3 | 13.01% | Best-fit Model<br>Time Series Decomposition-Multiplicative | MD3 | 9.78% |
| | AM4 | 13.03% | | MD4 | 10.68% |
| | AM5 | 12.00% | | MD5 | 8.88% |
| | AM6 | 12.94% | | MD6 | 11.82% |
| | AM7 | 14.05% | | MD7 | 10.90% |
| Pegel 's Classification No trend, Additive seasonality(NA) | NA3 | 15.66% | Time Series Decomposition-Additive | AD3 | 9.74% |
| | NA4 | 15.79% | | AD4 | 10.75% |
| | NA5 | 17.09% | | AD5 | 9.05% |
| | NA6 | 19.54% | | AD6 | 11.84% |
| | NA7 | 22.89% | | AD7 | 10.79% |
| Simple Exponential Method | SE | 11.77% | Pegel 's Classification No trend, Additive seasonality(AN) | AN | 12.12% |

Capacity Tool to generate the required resource forecast to manage required volume, as shown in Fig. 4. Based on the provided AHT or cycle time it provides the required capacity numbers to manage the forecasted volumes for next 5 days.

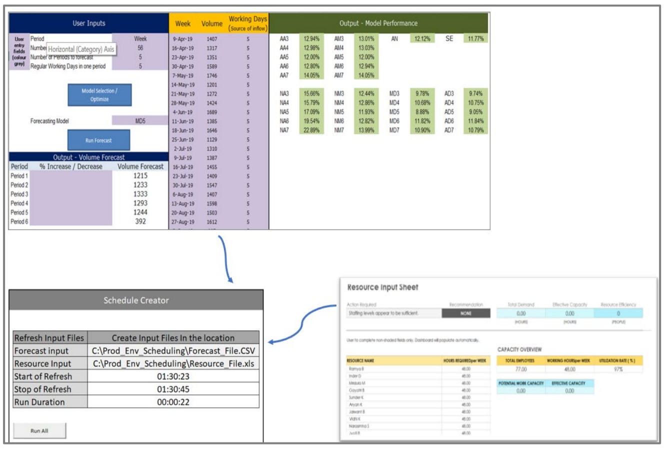



**Fig. 4.** Graphical output

*Note: Since the project is internal to the organization, algorithms cannot be included in the paper.*

*- Each model behaves differently for a different set of data. Hence, the model which performs well on one set of data might not work with a different set of data.*

After entering the data in the tool, the data is run through all the models that are embedded in the tool, and MAPE scores get generated. Along with the score, a graph is generated, providing visual impact. The graphical representation showing the MAPE score for all models is shown in Fig. 5.

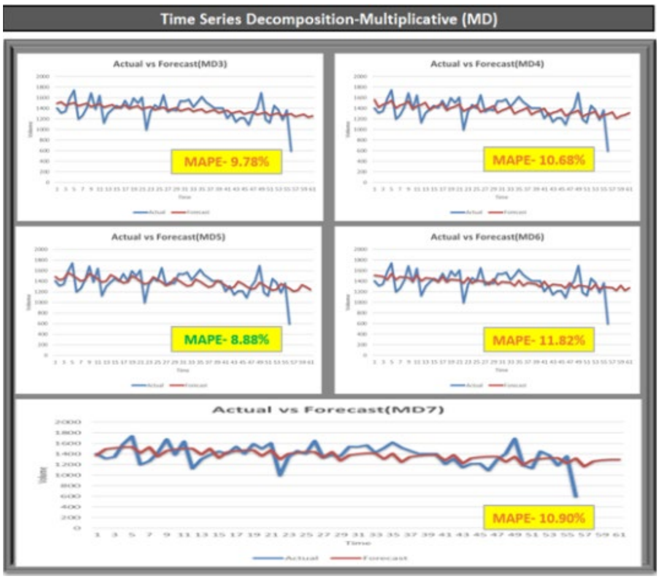



**Fig. 5.** Graphical output

## 8. Publishing Reports-Dashboard

Dashboard is generated for the consumption of the leadership. It provides visual representation of the metrics and provides available capacity against the volume forecast. Benefits of the dashboard:

- System sends an automated alert to the stakeholder for any variation in the defined metrics.
- Resource Manager: The model helps forecast resource utilization with flexible heat maps.

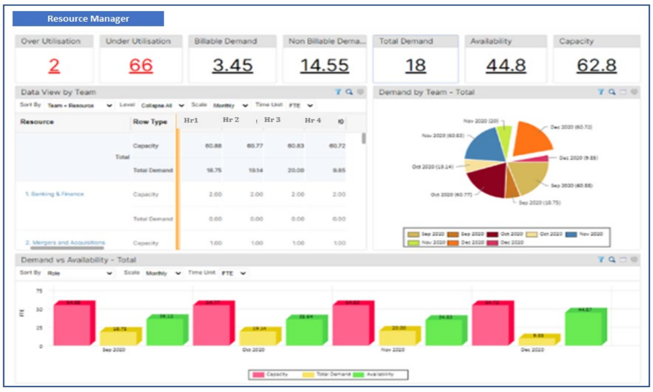


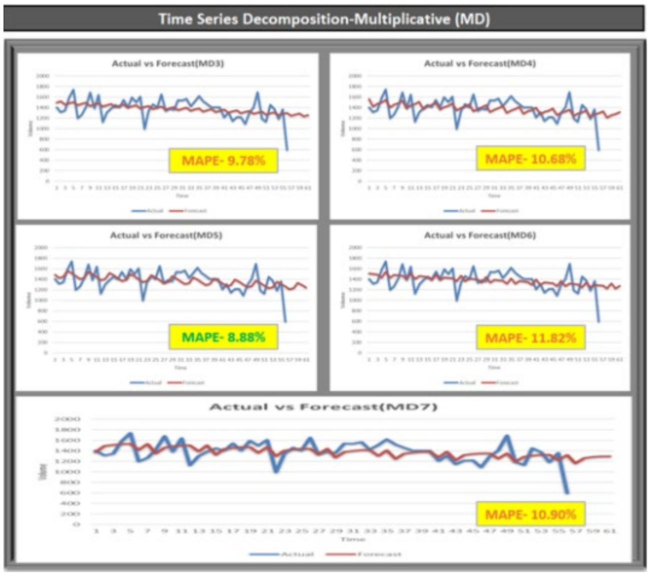

**Fig.6**. Graphical output

- Dashboards provide insights into revenue, cost, margins, etc.


## 9. Conclusion and Recommendation

Volume peaks and troughs are natural to all kinds of processes depending on the nature of the business; however, the critical part is to understand the data and tame it appropriately and drive valuable insights from the available data. By proactively planning for the variations, operations can plan to support volume spikes with limited resources and can plan accordingly to cater to the change in requirement. Development of a Forecasting and Capacity Planning model empowers operations to consistently forecast incoming volume for scheduling/rostering. A combination of past process-specific data, algorithmic forecasting, SME inputs, and modelling results in a forecast with a daily accuracy of up to 85% per month out and approximately 95-98% per week. Despite of unavailability of required tools and skill sets, the project team completed the challenge of developing the Forecasting and Capacity management tool within the stipulated timeframe.

Forecast generated by the tool, i.e., proactively highlighting any sudden volume spikes. Operations teams can work proactively to reduce potential delays in SLA metrics.

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