Summary Document: FWA Time Series Forecasting Model

1. Overview:

- The FWA Time Series Forecasting (TSF) model helps to predict how much internet data a user will use in the future on Fixed Wireless Access (FWA) devices.
- It uses a smart built-in forecasting method called ARIMA+, available directly in Google BigQuery. This means we can do all the predictions using simple SQL queries.
- The model predicts daily data usage for each user (IMSI) and helps to identify early signs of slow internet speed, especially when the user's connection changes from high-speed (QCI 8) to lower-speed (QCI 9) — which usually happens when users use too much data.

2. Why Forecasting is Needed?

- To predict monthly data usage trends.
- Identify network throttling risks.
- Help the AIOps Insight Platform manage resources and alert potential performance drops.
- Specifically detect when a user's QoS shifts from high priority (QCI 8) to low priority (QCI 9).

3. Model Use Case

The model forecasts future daily traffic for each FWA device (IMSI) to:

- Detect QCI transitions.
- Improve customer experience by avoiding unexpected slowdowns.
- Enable better capacity planning and network optimization.

4. Methodology – End-to-End Flow

Step 1: Raw Data Aggregation

- Pull from from_mobile_bytes and to_mobile_bytes fields from SDR logs.
- Aggregate daily total traffic for each user (IMSI).

Step 2: Cycle Start & Cumulative Calculation

- Identify plan cycle start and end dates.
- Calculate cumulative usage per cycle and per QCI level.

Step 3: Model Training (ARIMA+)

- Train model using 120 days of historical traffic.
- Model built in SQL using BigQuery's ML.FORECAST function.

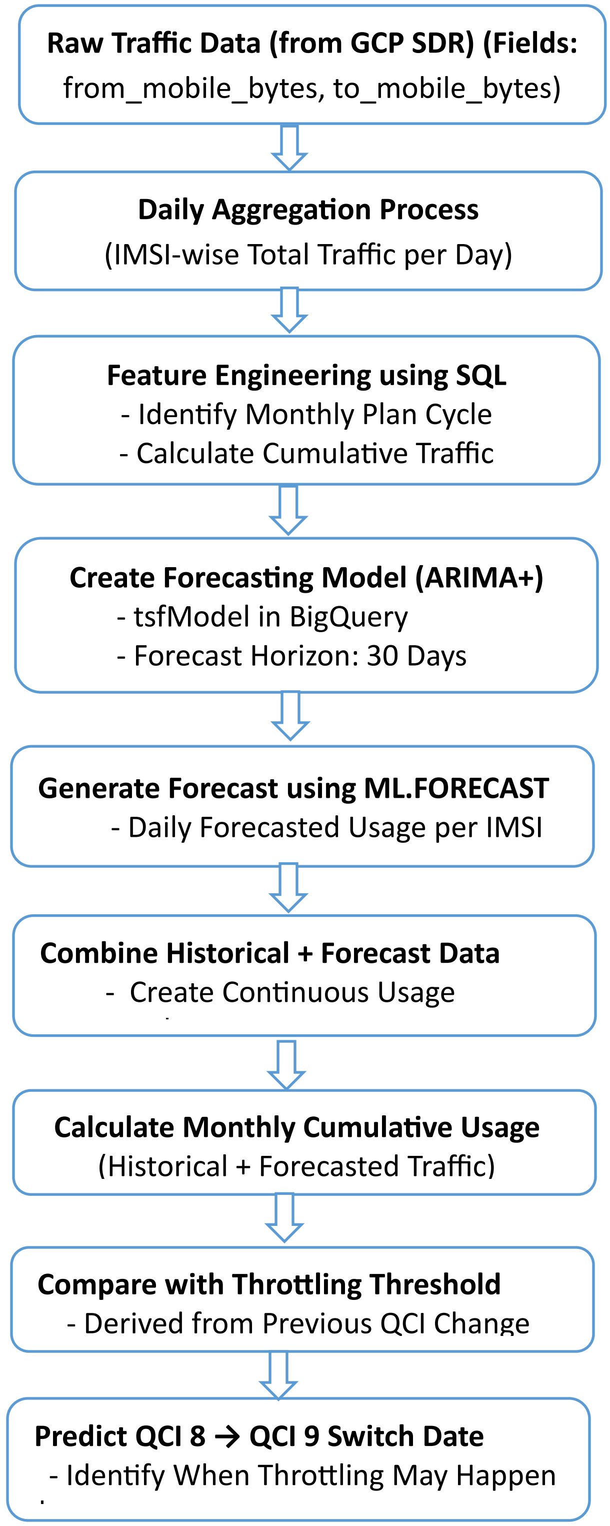
Step 4: Forecast Generation

- Predict 30 days of future traffic per IMSI.

Step 5: Post-Processing & QCI Throttling Detection

- Merge historical + forecasted data.
- Calculate cumulative usage in future month.
- Compare with historical QCI threshold to predict throttling day.

Flow diagram:



5. Model Architecture and Key Parameters

Parameter	Value
Model Type	ARIMA_PLUS (in BigQuery)
Forecast Horizon	30 Days
Confidence Level	95%
Data Frequency	Daily
Max Time Series Length	60 Days
Clean Spikes/Dips	Yes
Holiday Region	US
Decompose Time Series	Yes

6. Input & Output Parameters

- **Input Table (Aggregated Data):**

Name	Description
servedimsi	User Identifier (IMSI)
date	Daily Data Timestamp
totalTraffic	Sum of data usage (upload + download)

- **Output Table (Forecasted Data):**

Column Name	Description
forecast_timestamp	Date of Forecast
forecast_value	Predicted Data Usage
standard_error	Error in Forecast
prediction_interval_lower_bound	Lower bound of forecast range
prediction_interval_upper_bound	Upper bound of forecast range
confidence_interval_lower_bound	Lower bound of confidence interval
confidence_interval_upper_bound	Upper bound of confidence interval

7. Model Training and Forecasting

Create Model SQL:

```
CREATE OR REPLACE MODEL `tsfModel`
OPTIONS (
  model_type='ARIMA_PLUS',
  time_series_timestamp_col='date',
  time_series_data_col='totalTraffic',
  time_series_id_col=['servedimsi'],
  auto_arima=True,
  data_frequency='DAILY',
  max_time_series_length=60,
  horizon=30,
  auto_arima_max_order=5,
  clean_spikes_and_dips=True,
  holiday_region='US',
  adjust_step_changes=True,
  decompose_time_series=True
)
AS
SELECT servedimsi, date, totalTraffic FROM
`aggregatedTable`;
```

Forecast SQL:

SELECT * FROM ML.FORECAST(MODEL `tsfModel`, STRUCT(30 AS horizon, 0.95 AS = confidence_level));

Post-Processing – Predict QCI Change

Step 1: Detect Historical QCI Threshold

- Analyze when QCI changed from 8 → 9 in past cycles.
- Identify cumulative traffic at that point (threshold).

Step 2: Merge Historical + Forecast Data

- Create a single table with both real and forecasted values.

Step 3: Calculate Monthly Cumulative Forecast

- Calculate total monthly usage (historical + predicted).
- Compare it with the historical QCI threshold to predict the next throttling event.

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