



Baltimore/Washington International Airport (BWI)

Predicting Flight Delays & Forecasting Passenger Volume (2025–2026)

Executive Summary:

Baltimore-Washington International (BWI) Airport, a key East Coast transportation hub, faces increasing pressure to enhance efficiency, reduce delays, and anticipate passenger demand. To support proactive, data-driven decision-making, this report delivers two integrated analyses: (1) a classification model to predict flight delays, and (2) a time series forecast of monthly passenger traffic for the upcoming 12-month period from June 2025 to May 2026. These models are designed not merely for operational monitoring but to guide financial, staffing, and strategic planning at the executive level.

Methodology:

The first objective was to create a classification model capable of predicting delayed arrivals, defined as flights arriving 15 or more minutes late. Using 2023 flight-level data for training and validation and testing on 2024, I engineered a supervised learning pipeline with engineered time and weather features, airline identifiers, and aircraft type. After testing Logistic Regression, Decision Tree, Random Forest, XGBoost, and LightGBM, a Neural Network model emerged as the most suitable. Tuned to a 0.3 threshold, the final model achieved a precision of 0.382, recall of 0.508, and F1 score of 0.436 on the 2024 test set. The model's strength lies in its ability to flag high-risk flights while maintaining a reasonable false positive rate allowing airport operations to focus resources where they're needed most.

The second analysis focused on forecasting passenger traffic using a SARIMA model. I aggregated the T-100 dataset for all BWI arrivals and departures between 2000 and 2024. After verifying stationarity, seasonality, and autocorrelation structures, I trained a SARIMA(1,1,1)(1,1,1,12) model to reflect monthly periodicity. The forecast predicts stable and robust demand across the forecast window (June 2025 - May 2026), with monthly volumes ranging from approximately 1.86M to 2.46M passengers. The peak month is forecasted as July 2025, while the trough is February 2026. The confidence intervals remain tight for the short term, reinforcing reliability in the early months. This level of forecasting supports tactical decisions such as scheduling, vendor supply planning, and temporary staffing for high-traffic periods.

Key Findings:

Strategically, the predictive models offers BWI a chance to evolve from reactive to anticipatory operations. By identifying flights at high risk of delay, the airport can assign them to more flexible gates or build in operational buffers, thereby reducing cascading delays. Staff deployment for TSA, security, and ground crews can be calibrated to align with predicted high-traffic months, especially July and August. Forecasted volumes above 2M passengers per month also support expanded concession strategies and targeted marketing campaigns for retailers. Meanwhile, the lower confidence bound of ~1.7M passengers even in slower months like February 2026 underscores the need for consistent service quality and safety preparedness year-round.

I further explored KPIs required for strategic insight in 2024. BWI served approximately 25.2M total passengers in 2024 up from 24.4M in 2023, reflecting YoY growth of 3.5%. This includes both departures and arrivals aggregated. However, total scheduled flights declined slightly by -3.5% from 4,340 to 4,186, suggesting rising load factors or larger aircraft utilization. In 2024, Southwest (WN) continued to dominate carrier market share with 71%, followed distantly by Spirit (NK), Delta (DL), and American (AA). The top five domestic destinations by passenger volume were Atlanta (ATL), Orlando (MCO), Fort Lauderdale (FLL), Denver (DEN), and Boston (BOS), with ATL alone attracting over 890,000 passengers.

Strategic Recommendations: Leveraging Predictive Analytics to Drive Airport Value

The results from the delay prediction and passenger forecasting models present a clear opportunity for BWI to become a proactive, data-powered transportation hub. By embedding insights from machine learning and time series forecasting into operational, commercial, and strategic functions, the airport can boost efficiency, optimize passenger experience, and create new revenue streams.

1. Proactive Delay Risk Monitoring in the Airport Operations Control Center (AOCC)

To extract maximum value from the Neural Network classification model—designed to flag high-risk flight delays with a precision-optimized threshold ($\geq 30\%$)—BWI should integrate real-time predictions into the AOCC dashboard. This integration would enable targeted interventions before operational bottlenecks emerge.

Gate Flexibility Protocols: Assign flagged flights to gates with buffer capacity or low turnaround dependency to prevent ripple effects from delays. Concourse C, with its dense Southwest traffic, should be prioritized for pilot testing due to its high gate utilization.

Priority Resource Allocation: Equip security, ground handling, and baggage teams with early warnings on delayed flights, especially in weather-sensitive seasons like winter, to enable proactive deployment and improve on-time turnaround.

Passenger Notification Automation: Use digital signage and SMS alerts integrated with the delay risk engine to inform travelers of potential delays earlier, improving satisfaction and dispersing crowds near impacted gates.

2. Flexible Retail Agreements Based on Seasonal Demand Forecasts

The SARIMA model indicates that BWI will see peak monthly volumes of 2.4 million passengers in July 2025, with sustained highs through August and seasonal lows near 1.8 million in early 2026. These fluctuations support a retail strategy responsive to demand:

Revenue Sharing Clauses: Introduce tiered lease agreements for food, beverage, and retail vendors that adjust rent based on monthly footfall forecasts, ensuring rent aligns with sales opportunity.

Short-Term Activation Zones: Allow high-yield vendors (e.g., pop-up coffee kiosks, express wellness services) to operate temporary retail booths in high-traffic terminals such as Concourse A and E during summer months.

Terminal-Level Optimization: Reassign premium retail locations based on forecasted terminal volumes to ensure high-spending passengers have easy access to flagship vendors during peak periods.

3. Precision Staffing Strategy Anchored in Forecast Volatility

Rather than applying a flat staffing model, BWI should tailor workforce planning using SARIMA output at a monthly resolution to align labor budgets with predicted demand.

Rolling 3-Month Planning Horizon: Update TSA, custodial, and ramp agent staffing plans quarterly based on evolving forecast confidence intervals, minimizing overstaffing in low-demand months.

Concourse-Based Workforce Allocation: Allocate staff dynamically across terminals based on predicted load, for example, increasing presence in Concourse B and C during July–August peaks exceeding 2.3M passengers.

Vendor Contract Alignment: Use predicted volumes as leverage when negotiating seasonal staff contracts with security and baggage handling vendors, helping align labor costs with actual footfall.

4. Intelligent Gate Assignment to Reduce Bottlenecks

As load factors rise, traditional static gate assignments become insufficient. With predictive insight into both delay risk and passenger volume, BWI should adopt a dynamic gate assignment system:

Tiered Gate Allocation: Route long-haul or high-volume flights (e.g., ATL, DEN, BOS) to central, high-capacity gates with quick access to security and concessions, while relocating short-

haul flights to less congested outer gates.

Dynamic Recovery Time Scheduling: Build longer buffer windows for gates serving delay-prone flights, as predicted by the classification model, especially during high-traffic hours.

Gate Clustering by Carrier or Destination: Cluster flights from the same airline or to the same region (e.g., Florida-bound flights) in adjacent gates to streamline operations and reduce passenger confusion.

This adjustment can significantly reduce gate delays and terminal crowding.

5. Carrier Collaboration on Predictive Planning (Led by Southwest Partnership)

Southwest Airlines comprises over 70% of BWI's total departures and arrivals. Predictive collaboration with such a dominant carrier can produce shared operational benefits.

Joint Predictive Dashboards: Co-develop analytics dashboards that combine BWI's delay model outputs with Southwest's internal fleet and crew schedules to improve coordination.

Shared Readiness Protocols: Use monthly SARIMA forecasts to align both airport and airline staffing, gate usage, and contingency planning especially for holiday weekends and major travel surges.

FAA Joint Funding Opportunities: Collaborate on grant proposals under the FAA's Smart Airports program to fund infrastructure improvements justified by predictive analytics.

This strategic alignment ensures smoother operations and shared accountability during high-traffic periods.

6. Resilience Planning Based on Forecast Confidence Bands

While the SARIMA model projects stable passenger demand through mid-2026, forecast confidence intervals widen in later months. This uncertainty should guide contingency planning.

Dual Operational Playbooks: Develop two distinct plans, one based on upper-bound demand (up to 2.5M passengers) and one on lower-bound forecasts (as low as 1.7M)—to prepare for both high- and low-demand scenarios.

Contingency Budgeting: Allocate additional buffer budgets for customer service, terminal maintenance, and temporary staffing during volatile months, such as March–April 2026.

Quarterly Model Recalibration: Commit to retraining the SARIMA model every quarter using updated passenger data, ensuring decisions remain grounded in real-time trends and reducing reliance on outdated forecasts.

7. Real-Time Passenger Flow Optimization Using Historical & Predicted Volume Patterns

With high-resolution monthly passenger forecasts and granular historic trends by concourse and time-of-day, BWI can deploy intelligent crowd management systems to optimize passenger movement and service delivery.

Predictive Queue Allocation: Use predicted monthly volumes combined with time-of-day flight schedules to dynamically adjust TSA checkpoint staffing and lane availability, reducing wait times during spikes.

Smart Signage & Wayfinding: Deploy AI-enabled signage that changes dynamically based on passenger heatmaps, redirecting passengers during crowding at escalators, food courts, or restrooms.

Concourse-Specific Load Balancing: Shift airline check-in or baggage drop-off zones in anticipation of overcrowding, especially in Concourse B during summer peaks, to balance footfall and avoid service bottlenecks.

This recommendation ties directly to both customer satisfaction and operational efficiency, and showcases BWI's commitment to leveraging technology for a seamless passenger journey.

Conclusion

The predictive models developed in this report equip BWI with actionable tools to anticipate delays and forecast passenger demand with confidence. These insights go beyond operational awareness—enabling smarter gate assignments, seasonal staffing, retail planning, and strategic carrier collaboration. By embedding these models into decision-making, BWI can enhance efficiency, improve passenger experience, and sustain growth in an increasingly dynamic travel landscape.

Dashboard:



Total Passengers
(2024)

25217117

Growth(%)
(Passenger)

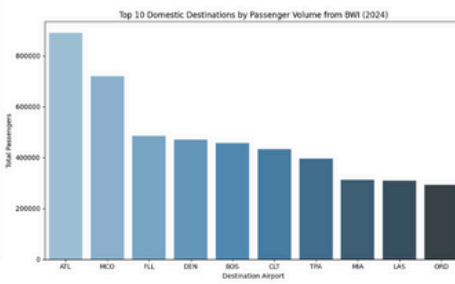
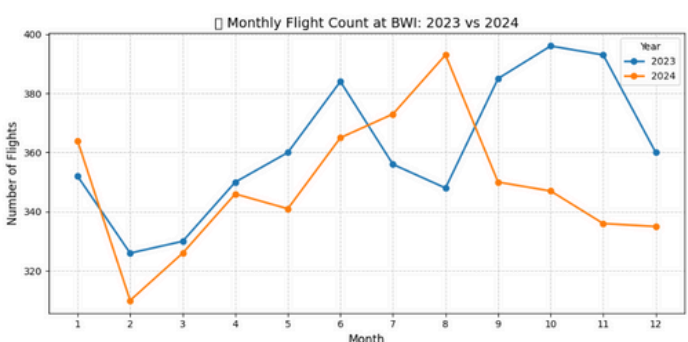
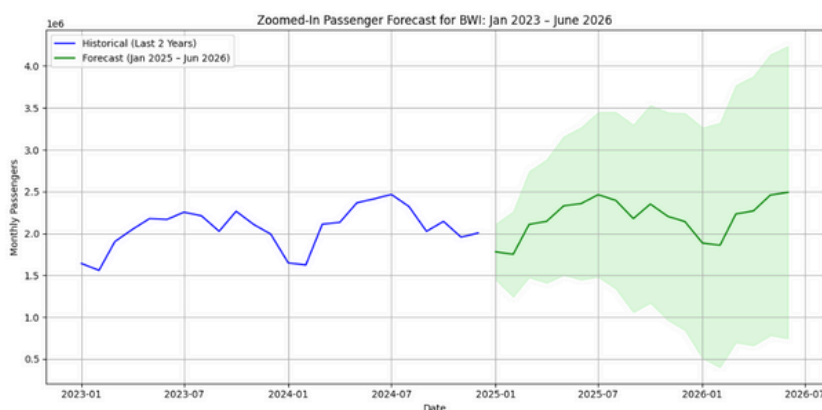
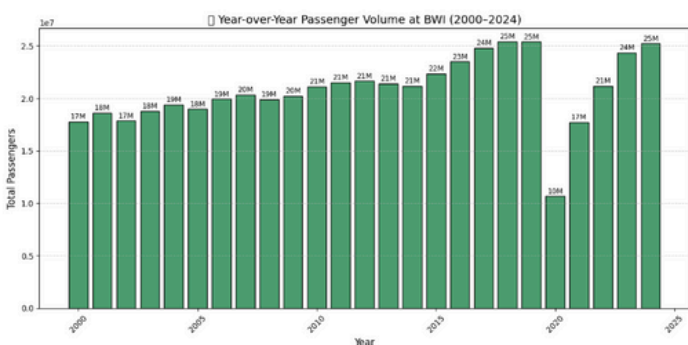
3.53

Total Scheduled
flights(2024)

4186

Growth(%)
(Flights Scheduled)

-3.55



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