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Predictive Analytics for Ground Handling Turnaround Delays:

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ABSTRACT

Aircraft turnaround, the sequence of ground handling activities that occur between an aircraft's arrival at and departure from a stand, is a frequent but poorly disaggregated source of flight delay, since most airline delay-coding systems record ground handling as a single generic cause rather than breaking it into its constituent sub-processes. This study conducts a secondary analysis of published research and publicly available operational datasets, including Bureau of Transportation Statistics delay-cause records, EUROCONTROL standard turnaround time reference data, SITA baggage mishandling reports, and Airport Council International ground handling benchmarks, to identify which ground handling sub-processes, namely baggage loading, refuelling, cabin cleaning, pushback coordination, and staff availability, most strongly predict turnaround and downstream flight delay. Rather than collecting new flight-level data, the paper synthesises modelling approaches, feature-importance findings, and reported accuracy figures from a cross-section of recent regression and classification studies. The synthesis shows that ground infrastructure readiness and baggage-specific features consistently rank among the strongest predictors of both turnaround duration and downstream departure delay, and that cascaded, milestone-based prediction frameworks outperform single-point estimates as a turnaround progresses. The paper concludes that a disaggregated, sub-process-level view of ground handling offers materially more actionable insight for airport and airline operations than the aggregated "ground handling" delay-cause category currently used in most delay statistics, though standardised, cross-airport sub-process data remains scarce.

Keywords: *turnaround time; ground handling; flight delay prediction; machine learning; baggage handling; airport operations*

1.INTRODUCTION

An aircraft only generates revenue while it is in the air, yet every flight depends on a short, tightly choreographed window on the ground during which passengers disembark and board, baggage and cargo are unloaded and reloaded, the cabin is cleaned, the aircraft is refuelled, catering is replenished, and the aircraft is pushed back from the stand. This window, known as the turnaround, typically lasts between twenty-five and forty-five minutes for a narrow-body aircraft, and every one of its constituent sub-processes must complete, largely in sequence or in tightly constrained parallel, before departure can occur. Because turnaround time is compressed and interdependent, a delay in any single sub-process, a late baggage cart, a fuel truck queued behind another aircraft, a cabin cleaning crew short-staffed for a shift, can consume the schedule buffer entirely and produce a departure delay that then propagates through the rest of that aircraft's rotation for the remainder of the day.

Despite the operational importance of this window, the way ground handling delay is recorded and studied has a significant blind spot. Airline and regulatory delay-coding systems, including the cause categories used in flight-level delay statistics published by national aviation authorities, typically treat ground handling as a single aggregated cause code, indistinguishable from whether the actual bottleneck was baggage loading, refuelling, cabin cleaning, or crew and staff availability. This is a meaningful limitation: an airport or ground handling agent trying to reduce delay has very different levers available depending on whether the binding constraint is baggage belt throughput, fuel truck scheduling, cleaning crew staffing, or pushback tug availability, and an aggregated delay cause code gives no guidance as to which lever to pull.

A growing body of machine learning research has begun to open up this aggregated category by modelling

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individual turnaround sub-processes and milestone times directly, using flight-level, apron-level, and even video-surveillance data. In parallel, a separate strand of operations research literature has long studied ground handling scheduling and resource allocation using detailed mathematical optimisation models, though this literature has historically been framed around scheduling efficiency rather than around identifying which sub-process most strongly drives delay in a way that is legible to airline and airport managers. This paper draws together both strands, together with publicly available secondary data sources describing ground handling performance, in order to build a more complete, business-facing picture of which ground handling factors most strongly predict turnaround and downstream flight delay, and to make the case for a more disaggregated approach to ground handling delay analytics than either strand currently offers on its own.

2.NATURE AND SCOPE OF THE STUDY

This study is a descriptive, desk-based secondary analysis rather than an empirical exercise built on newly collected turnaround-log data. The unit of analysis is twofold: published research articles describing turnaround and ground handling prediction models, treated as individual data points to be compared and synthesised, and publicly available secondary datasets and benchmark reports describing ground handling performance at an aggregate level, used to characterise the operational context within which these models are applied. This design was adopted because airline- and ground-handler-specific turnaround logs, timestamped by individual sub-process, are commercially sensitive and not published in the detail that a primary study of this kind would require; secondary analysis of published research and publicly available aggregate statistics is the feasible route to a broad, evidence-grounded account of the topic.

2.1 Secondary data sources considered

Five categories of publicly available secondary data are drawn on to frame the study, each contributing a different layer of context. Bureau of Transportation Statistics (BTS) flight-level data for United States carriers provides delay-cause breakdowns at the individual flight level, including the aggregated "late aircraft" and carrier-attributable delay categories within which most ground handling delay is currently subsumed. EUROCONTROL's standard turnaround time reference material documents typical minimum and buffer turnaround durations by aircraft type and airport category across the European network, providing a benchmark against which observed or modelled turnaround durations can be compared. SITA's annual Baggage IT Insights reporting tracks global baggage mishandling rates and their principal causes, offering an industry-wide view of the baggage sub-process specifically. Airport Council International (ACI) ground handling performance benchmarking material provides cross-airport comparators for service quality and turnaround efficiency. Finally, DGCA India's published airport performance and delay statistics offer an India-specific angle, allowing the largely North American and European academic literature reviewed in this study to be considered alongside a rapidly growing, high-density South Asian aviation market with different infrastructure and staffing constraints.

The scope of the review is bounded in three further ways. Thematically, the study restricts itself to studies and datasets that either model turnaround or ground handling sub-process durations directly, or that provide delay-cause data granular enough to distinguish ground handling from other delay categories such as weather, air traffic control, or crew scheduling; pure air traffic flow management and airspace capacity studies are excluded unless they explicitly model ground-side turnaround. Temporally, the review concentrates on studies published within roughly the last six to seven years, the period in which machine-learning-based turnaround and milestone-time prediction became a distinct and active research area alongside the older, mathematically-oriented ground handling scheduling literature. Sectorally, the underlying studies draw predominantly on major hub airports in Europe, the United States, and East Asia, which shapes the applicability of specific reported figures to smaller or differently structured airports, including many in the Indian market referenced through DGCA data.

Within these boundaries, the variables examined across the reviewed studies include turnaround sub-process durations (baggage loading and unloading time, refuelling time, cabin cleaning duration, catering time, pushback and tow time), flight-level features (scheduled and actual arrival and departure times, aircraft type, route, passenger and baggage load), and contextual features (weather, staff and ground equipment availability, stand

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allocation, time of day). The rationale for including this mix is that it mirrors the feature space used across the reviewed literature and allows the sub-process-level findings of otherwise disparate studies to be compared on a common conceptual footing.

3.REVIEW OF LITERATURE

3.1 The research gap: two disconnected streams

The existing literature relevant to ground handling delay can be read as falling into two largely separate streams that rarely cite or build directly on one another. The first stream is operations research: mathematically dense scheduling and resource allocation models concerned with optimally assigning ground crews, vehicles, and equipment across competing aircraft turnarounds, typically framed around minimising total handling time or resource cost rather than around explaining which sub-process is the dominant driver of delay in a way that is legible to a non-specialist airline or airport manager. The second stream is airline delay prediction: a large body of machine learning research, reviewed extensively elsewhere, that predicts overall flight delay from schedule, weather, and carrier features, but that treats ground handling as a single generic delay-cause category rather than decomposing it into baggage, fuelling, cleaning, or staffing sub-processes. This paper's contribution is to draw together a smaller, more recent body of work that sits between these two streams, work that models turnaround sub-processes directly using machine learning, and to argue that this middle ground remains comparatively underdeveloped relative to either of its neighbouring streams.

3.2 Turnaround time and milestone prediction

A foundational contribution in this space developed a turnaround sub-processes fusion model that forecasts overall aircraft ground time incrementally, using a heuristic, classification-based method built from real-life turnaround records at a major airport, on the basis that the duration of each sub-process, baggage loading, deplaning and boarding, and fuelling, can be estimated from the aircraft's concrete payload characteristics even when the exact start time of each sub-process is difficult to predict in advance due to gate, resource, or air traffic constraints. Related work modelling weather's effect on turnaround and departure performance found that machine learning approaches could quantify the relationship between deteriorating weather conditions and reduced airport performance with a prediction accuracy exceeding ninety percent for departure movements, underlining that exogenous, non-ground-handling factors interact with, rather than replace, ground handling as a source of delay.

A more recent and directly relevant contribution proposed a cascaded, multi-output gradient boosting regression tree model to dynamically predict the milestone times of individual turnaround activities, with predictions continuously updated as the turnaround itself progresses, using a comprehensive feature set combining flight-related attributes with information carried forward from earlier predictions within the same turnaround. This study reported an initial prediction accuracy above eighty percent within five minutes of the actual activity time, improving as the turnaround advanced until more than sixty percent of activities achieved above ninety-five percent accuracy within the same five-minute threshold, and, importantly for the present review, found that feature importance differed significantly across different turnaround milestones, meaning that no single feature or sub-process dominates prediction uniformly across the whole turnaround.

3.3 Target off-block time and collaborative decision-making

A separate but closely related strand of literature addresses the prediction of Target Off-Block Time (TOBT), the time set by an airline or ground handler for departure that reflects delays attributable to ground handling operations and that airport collaborative decision-making systems depend on for accurate pre-departure sequencing. A study developing probabilistic machine learning models for turnaround time and last TOBT values across four major European airports, Prague, Geneva, Arlanda, and Fiumicino, demonstrated that reliable turnaround and TOBT prediction under nominal operating conditions is achievable using operational data alone, without requiring the kind of granular sub-process instrumentation that some other studies in this space rely on. This work is significant for the present review because it shows that useful sub-process-adjacent prediction is possible even where an airport's own data does not natively separate baggage, fuelling, and cleaning into distinct

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logged fields, an important practical consideration given how rarely such granular data is made public.

3.4 Ground resource allocation and arrival time uncertainty

A further contribution examined how uncertainty in aircraft arrival time itself, an input that ground handling planning depends on but that ground handlers do not control, affects downstream ground resource allocation. This study developed a multiple linear regression model and a multilayer-perceptron-based model to predict round-trip arrival times and to classify arrival delays by severity, reporting a root-mean-square error of eight minutes per origin-destination pair and an average classification accuracy of 93.5 percent for arrival delay severity. The practical implication for ground handling analytics is that a meaningful share of apparent "ground handling delay" may in fact originate upstream, in uncertain or late arrival times that compress the available turnaround window before any ground handling sub-process has even begun, a distinction that aggregated delay-cause statistics are not able to draw out.

3.5 Baggage handling as a distinct sub-process

Baggage handling receives disproportionately little dedicated machine learning attention relative to its operational and financial significance; industry reporting has put the global cost of baggage mishandling to the aviation industry at roughly five billion dollars in a single recent year, driven substantially by conveyor and sortation equipment failures at busy hub airports operating tens of thousands of individual conveyor units. A recent AI predictive-maintenance approach addressed this specific sub-process by applying machine learning to real-time sensor data, including vibration, temperature, current draw, and acoustic signals, to detect developing conveyor and motor faults before they cause an outright failure, reporting that such approaches can substantially reduce baggage-system-driven delay by catching degradation weeks before a component would otherwise fail. Complementing this equipment-focused view, a recent multi-source flight delay prediction framework explicitly integrated baggage-handling information alongside flight schedules, surveillance data, weather, and airport-specific features, and found that adding baggage-specific features improved departure delay prediction error by close to twenty-five percent, with XGBoost identified as the best-performing algorithm for departure delay and Random Forest for short-term arrival delay prediction. This is one of the clearest pieces of direct evidence in the reviewed literature that baggage handling, modelled as its own distinct feature set rather than folded into a generic ground handling category, carries genuine, separable predictive power.

3.6 Structural and critical-point approaches to turnaround delay

A conceptually distinct contribution proposed a framework built around identifying specific critical time thresholds within the turnaround at which small local disturbances propagate into disproportionately large, system-wide disruption, arguing that turnaround delays are not random but structurally determined by the sequencing and interdependency of sub-processes. Case analyses within this framework illustrated the point with concrete examples, including a fuelling delay that initially caused nine minutes of disruption but was reduced to under four minutes once the fuelling sequence was reordered around the identified critical threshold, and a baggage mismatch scenario in which restructuring the loading sequence eliminated a systemic bottleneck entirely. While this work is framed mathematically rather than as a conventional supervised learning exercise, its practical implication reinforces a theme found throughout the more data-driven studies reviewed above: the sub-process at which a delay originates, and precisely when within the turnaround sequence it occurs, matters more to the size of the resulting disruption than the raw duration of the delay itself.

3.7 Automated detection of ground service activities

A final relevant strand addresses a practical precondition for any of the modelling approaches above: the availability of accurate, timestamped data on when each ground handling sub-process actually starts and finishes. A deep learning and computer vision-based system was developed to automatically detect, track, and monitor ground service actions during aircraft turnarounds using video surveillance footage from a single fixed apron camera, successfully identifying and timing primary ground services without requiring dedicated sensors on each piece of ground support equipment. Related work has applied similar computer-vision techniques specifically to predict push-back time from visual monitoring of turnaround activity, and industry deployments at major airports

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have reported using aircraft-generated and apron-operational data to refine turnaround processes and reduce passenger delay. This strand of the literature matters for the present review because it addresses the data-availability constraint noted throughout the discussion above: sub-process-level ground handling analytics of the kind this paper argues for depends on exactly this kind of automated, granular timestamping, which is now technically feasible even where an airport's existing systems do not natively record it.

Taken together, the literature reviewed here confirms the research gap this paper set out to address. Operations research contributes rigorous scheduling and resource allocation models but rarely frames its output in terms of which sub-process is the dominant driver of delay in language accessible to airport or airline management. Airline delay prediction research contributes large-scale, well-validated overall delay models but almost universally treats ground handling as a single undifferentiated cause category. The smaller body of turnaround-specific and baggage-specific work reviewed in this section begins to bridge that gap, but remains fragmented across different airports, data sources, and modelling frameworks, with no widely adopted standard for reporting sub-process-level feature importance in a form that would allow direct comparison across airports or airlines.

4.OBJECTIVES OF THE STUDY

The specific objectives guiding this review are as follows:

1. To identify and categories the ground handling sub-processes, baggage loading, refueling, cabin cleaning, pushback, and staff availability, that recent machine learning literature has modelled as distinct predictors of turnaround and downstream flight delay.
2. To compare reported feature-importance findings across studies in order to establish which sub-process or combination of sub-processes most consistently emerges as the dominant driver of turnaround delay.
3. To examine how publicly available secondary data sources (BTS, EUROCONTROL, SITA, ACI, and DGCA India) characterise ground handling performance at an aggregate level, and to assess how well this aggregate view aligns with sub-process-level findings from the academic literature.
4. To evaluate the extent to which existing research bridges the operations-research and airline-delay-prediction streams identified as the study's central research gap.
5. To surface data-availability and standardisation gaps that currently limit sub-process-level ground handling analytics, and to propose directions for future research and data collection that could close them.

5.DISCUSSION OF RESULTS

The synthesis of findings across the reviewed studies offers a reasonably clear, if still incomplete, answer to which ground handling sub-processes most strongly predict turnaround and downstream delay. Ground infrastructure readiness and scheduled turnaround adequacy recur across multiple studies as leading predictors of departure delay, with one recent ensemble-learning study explicitly identifying scheduled turnaround and ground infrastructure readiness as the primary determinants of delay duration and describing a pronounced knock-on effect in which narrow transition windows between consecutive flights fail to absorb even modest sub-process delays. This finding is echoed structurally by the critical-threshold framework discussed above, which similarly emphasises that the timing of a disturbance relative to the turnaround sequence, not merely its raw duration, determines how far it propagates.

Baggage handling stands out as the sub-process with the clearest, most directly quantified independent contribution among those specifically named in this study's scope. The reviewed multi-source delay-prediction framework's finding that baggage-specific features improved departure delay prediction error by close to twenty-five percent is, within the literature surveyed here, the single most concrete piece of evidence that a named ground handling sub-process carries separable predictive power once it is modelled explicitly rather than absorbed into an aggregated ground handling category. This is reinforced from a different angle by industry reporting on the scale of baggage-system-driven disruption and by predictive-maintenance research targeting conveyor and sortation equipment specifically, both of which point toward equipment reliability, rather than staffing or scheduling alone, as an important and separately addressable component of baggage-related delay.

Evidence on refuelling, cabin cleaning, and pushback specifically is comparatively thinner and less directly

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quantified in the literature reviewed here relative to baggage handling and general ground infrastructure readiness. The turnaround sub-processes fusion model and the cascaded milestone-prediction study both model these sub-processes as part of a broader turnaround sequence and both report that feature importance shifts meaningfully across different milestones, implying that fuelling- or cleaning-specific delay drivers likely differ from baggage-specific ones, but neither isolates a fuelling- or cleaning-specific effect size in the way the baggage-focused study does for baggage. The critical-threshold framework's fuelling case study, showing a reduction from nine minutes of disruption to under four minutes through sequence reordering, is suggestive but framed as an illustrative case analysis rather than a generalisable statistical finding. This asymmetry in the depth of evidence available for different sub-processes is itself an important and directly policy-relevant finding of this review: it suggests that baggage handling is currently the best-evidenced entry point for airlines and ground handlers seeking to act on sub-process-level delay analytics, while refuelling, cleaning, and pushback remain comparatively under-researched despite plausibly contributing meaningfully to overall turnaround delay.

On the question of upstream versus ground-side delay origin, the arrival-time-prediction literature reviewed above adds an important qualifying note to any sub-process-level analysis: a share of what appears in delay statistics as ground handling delay may originate in uncertain or late aircraft arrival, which compresses the turnaround window before any ground handling activity has begun. This means that a purely ground-side view of turnaround delay, however well disaggregated by sub-process, risks over-attributing delay to ground handling teams for disruption that in fact originates in upstream schedule or air traffic variability, a distinction that the aggregated BTS-style "late aircraft" and ground-handling delay-cause categories referenced in this study's secondary data sources do not currently allow analysts to draw cleanly.

With respect to the central research gap this study set out to address, the reviewed literature confirms that a genuinely integrated, sub-process-level, business-facing view of ground handling delay remains underdeveloped. The operations research tradition offers rigorous scheduling and resource allocation methods but is rarely evaluated in terms of which sub-process drives delay in a form legible to non-specialist airport or airline management; the mainstream airline delay prediction literature offers large, well-validated models of overall delay but almost uniformly treats ground handling as an undifferentiated cause code; and the smaller, more recent body of turnaround- and baggage-specific work reviewed in this paper, while promising, is fragmented across different airports, feature sets, and reporting conventions, with no widely shared standard for comparing sub-process feature importance across studies. Advances in automated, camera- and sensor-based detection of ground service activity, reviewed above, suggest that the data-availability barrier to closing this gap is increasingly a matter of adoption rather than of fundamental technical feasibility, which is an encouraging signal for the direction future research in this area might usefully take.

In summary, the evidence reviewed here indicates that ground infrastructure readiness and baggage-specific features are, among the sub-processes considered in this study, the most consistently and directly evidenced predictors of turnaround and downstream flight delay, while refuelling, cabin cleaning, pushback, and staff availability remain plausible but comparatively under-quantified contributors given the current state of published research. Bridging the operations-research and airline-delay-prediction literatures through more granular, sub-process-level, and cross-airport standardised data, of the kind partially available through BTS, EUROCONTROL, SITA, ACI, and DGCA reporting but not yet consistently linked to flight-level outcome data, represents the most valuable direction for future work in this area.

Table 1: Summary of Reviewed Studies

Study focus	Method(s) used	Key reported result	Data scope
Turnaround sub-process fusion	Heuristic classification-based fusion model	Incremental ground time forecasting from payload data	Single major airport

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Weather impact on turnaround	ML classification, meteorological + flight data	>90% accuracy for departure movements	Airport operational + weather data
Cascaded milestone prediction	Multi-output cascaded gradient boosting	>80% accuracy within 5 min, improving to >95%	Study airport CDM data
TOBT / turnaround prediction	Probabilistic machine learning models	Reliable TOBT prediction under nominal conditions	Prague, Geneva, Arlanda, Fiumicino
Arrival time uncertainty	Multiple linear regression, MLP classification	RMSE 8 min; 93.5% delay-severity accuracy	Round-trip origin-destination pairs
Multi-source delay + baggage	XGBoost, Random Forest, multi-source fusion	Baggage features cut MSE by ~25%	Schedules, ADS-B, weather, baggage data
Baggage system predictive maintenance	Sensor-based ML fault detection	Early fault detection weeks ahead of failure	Conveyor/sortation IoT sensors
Critical-threshold structural model	Critical Minute Theorem (structural/algebraic)	Fuelling disruption cut from 9 to <4 min via reordering	Case-study turnarounds
Automated ground service detection	Deep learning + computer vision (video)	Accurate detection/timing of ground services	Apron camera surveillance

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