Risk Analysis and Safety Decision-Making in Commercial Air Transport Operations

PhD Thesis

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AUTORIZAN:

La presentación de la Tesis Doctoral titulada

RISK ANALYSIS AND SAFETY DECISION-MAKING IN COMMERCIAL AIR TRANSPORT OPERATIONS

realizada por D. Eduardo Sánchez Ayra bajo mi inmediata dirección y supervisión en el Departamento de Estadística e Investigación Operativa y que presenta para la obtención del grado de Doctor por la Universidad Rey Juan Carlos.

En Móstoles, a 31 de mayo de 2013

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INFORMA:

Que la Tesis Doctoral titulada

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Ha sido realizada por D. Eduardo Sánchez Ayra bajo la dirección y supervisión de D. David Ríos Insua y D. Javier Cano Cancela y que el Departamento ha dado su conformidad para que sea presentada ante la Comisión de Doctorado.

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Antonio Alonso Ayuso

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List of Abbreviations

ALARP As Low As Reasonably Practicable

ALD Actual Landing Distance

AOM Aircraft Operating Manual

ATFM Air Traffic Flow Management

AWOP All Weather Operations Panel

BTV Brake-To-Vacate

CEO Chief Executive Officer

CIAIAC Comisión de Investigación de Accidentes e Incidentes de Aviación Civil

CODA Central Office for Delay Analysis

CS Certification Specifications

DOC Direct Operating Costs

EASA European Aviation Safety Agency

EGPWS Enhanced Ground Proximity Warning System

EU European Union

EUR Euros

FAA Federal Aviation Administration

FCP Fuel Carriage Penalty

FHA Functional Hazard Analysis

FSF Flight Safety Foundation

GPS Global Positioning System

GS Glide Slope

G/A Go-Around

HFACS Human Factors Analysis and Classification System framework

HRA Human Reliability Analysis

HUD Head-UP Display

IAS Indicated AirSpeed

IATA International Air Transport Association

ICAO International Civil Aviation Organization

ICT Information and Communication Technology

ILS Instrument Landing System

IMC Instrument Meteorological Conditions

kt nautical miles per hour (knots)

LD Landing Distance

LDA Landing Distance Available

lm Linear Model

Lp/Hc Low probability/High Consequence

LT Local Time

MCMC Markov Chain Monte Carlo

MTOM Maximum Take Off Mass

MTOW Maximum Take Off Weight

OPS Operations

NASA National Aeronautics and Space Administration

RLD Required Landing Distance

ROP Runway Overrun Protection

ROW Runway Overrun Warning

Rwy Runway

R/D Rate Of Descent

SARP Standard And Recommended Practices

SAS Scandinavian Airlines

SMM Safety Management Manual

SMS Safety Management System

SOP Standard Operational Procedures

SPI Safety Performance Indicator

SPT Safety Performance Target

SSP State Safety Programme

Stab Stabilized

TD Touch Down

TLS Target Level of Safety

TOR Tolerability Of Risk

TOWS Take Off Warning System

TDZ Touch Down Zone

Unst Unstabilized

US United States

Vapp Final Approach Speed

Vref Reference Target Threshold Speed

VMC Visual Meteorological Conditions

SLG Safe Landing Guidelines

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Resumen

El primer vuelo de la aviación comercial tuvo lugar el 1 de enero de 1914 en Florida, EE.UU. Casi 100 años después, aterrizan a diario en el mundo unos 100,000 vuelos, convirtiéndose la aviación, además, en el medio de transporte más seguro. Según la Asociación Internacional de Transporte Aéreo (IATA), el año 2012 presentó la tasa de accidentes más baja de la historia de la aviación, con 1 accidente por cada 5 millones de operaciones. Desafortunadamente, dicha tasa de accidentes no está homogéneamente distribuida en las diferentes regiones del mundo: la tasa más baja corresponde a EE.UU, y la más alta, casi 30 veces superior, al continente africano. Además, en lo que respecta al estudio y análisis de dichos sucesos, la aviación comercial presenta un desafío adicional: los incidentes y accidentes aéreos son eventos poco probables, pero de consecuencias que pueden llegar a ser potencialmente catastróficas. En este contexto, la industria aeronáutica, considerada estratégica por la inmensa mayoría de los estados, prevé que el número de pasajeros transportados se duplique en 2030, llegando a los 6,000 millones. Por ello, es de vital importancia para la sociedad que se siga incrementando continuamente el nivel de seguridad operacional (*safety*). Sin embargo, en los últimos años la tasa de accidentes a nivel mundial presenta un comportamiento relativamente estable. Para algunos autores, como Vasigh et al. (2008), esto podría deberse a que se ha alcanzado el equilibrio económico en materia de seguridad operacional, es decir, un punto tal que los beneficios que potencialmente podrían aportar las medidas encaminadas a incrementar los actuales niveles de seguridad se ven contrarrestados por los costes económicos de implementación. Junto a esto, y aunque ha habido una clara evolución en cuanto a la gestión de la seguridad operacional se refiere, algunos autores critican el actual enfoque sobre gestión del riesgo adoptada por la Organización de Aviación Civil Internacional (ICAO, en sus siglas en inglés), tachándolo de simplista y poco fundamentado desde el punto de vista científico, véase, por ejemplo, Thomas (2012). Por todas las razones previamente mencionadas, parece necesario abrir nuevas vías de investigación, aportando nuevas ideas y herramientas metodológicas, dando de esta forma un nuevo impulso al análisis de riesgos y la toma de decisiones en el ámbito de la seguridad operacional.

Antecedentes

Ningún medio de transporte es absolutamente seguro. Por pequeña que sea, siempre existirá una cierta probabilidad de que, en un momento dado, ocurra un incidente o accidente con consecuencias no deseables: siempre existirá cierto “riesgo”. En otras palabras, no todos los riesgos pueden ser eliminados, de la misma manera que no todas las medidas mitigadoras que podamos concebir son económicamente viables. Bajo este punto de vista, en los últimos años, el concepto de seguridad operacional ha sufrido una notable evolución, véase ICAO (2009). Desde una posición tradicional en la que máximas como “la seguridad es lo primero y debe garantizarse a cualquier precio” eran indiscutibles, la aviación comercial ha aceptado una visión mucho más cercana a lo que hoy conocemos como gestión del riesgo. Aunque el análisis de riesgos empezó a aplicarse en la industria aerospacial norteamericana a principios de los años sesenta, véase Stamatelatos et al. (2002), no fue hasta el año 2006 cuando la ICAO editó, de forma oficial, su primer documento sobre la gestión del riesgo, véase ICAO (2006b). Sin embargo, a partir de su publicación, su implantación ha sido relativamente rápida y, al menos oficialmente, ampliamente aceptada tanto por las autoridades aeronáuticas como por la mayoría de explotadores y proveedores de servicios. Tal es así que en el año 2009 se publicó una nueva actualización de este documento y, a mediados de 2012, el Consejo Rector de la ICAO propuso oficialmente un nuevo anexo sobre la gestión de la seguridad operacional, denominado Anexo 19. Por tanto, estos últimos seis años han supuesto un cambio significativo en la forma de gestionar la seguridad aérea, más aún si tenemos en cuenta que la ICAO no había editado ningún nuevo anexo en los últimos 30 años.

En lo que respecta a la metodología utilizada, los estudios clásicos sobre la gestión del riesgo tenían un enfoque eminentemente frecuentista, en el que sólo se tenía en cuenta la información recogida a partir de los datos y donde, por el contrario, no tenían cabida la subjetividad inherente referida a los parámetros del modelo o la opinión del experto. Pero esta tendencia también está cambiando, y desde hace algunos años, han empezado a publicarse trabajos de autores que emplean la inferencia bayesiana en el campo del análisis de riesgos y la toma de decisiones en la industria aerospacial y aeronáutica en general, véase Dezfuli et al. (2009). Sin embargo, esta metodología aún no se ha extendido a la gestión de la seguridad operacional relacionada con la aviación comercial.

En esta Tesis proponemos un enfoque bayesiano a la hora de analizar el riesgo existente en tres sucesos relevantes en el transporte aéreo de pasajeros como son: (1) el despliegue involuntario de rampas de evacuación durante la operación normal del avión; (2) situaciones en las que los pilotos se enfrentan a la gestión de una cantidad insuficiente de combustible a bordo, debido a demoras provocadas por congestión de tráfico aéreo durante la fase de aproximación; y (3) salidas por el final de pista durante el aterrizaje. Hemos modelizado estos casos prácticos en detalle, y hemos empleando distintas herramientas estadísticas y de investigación operativa para resolverlos. La inferencia bayesiana, los métodos de simulación, en especial aquéllos basados en cadenas de Markov, y la optimización Montecarlo han sido algunas de las herramientas básicas que hemos usado en la Tesis a la hora de apoyar la toma de decisiones sobre las medidas mitigadoras que se han propuesto en cada uno de los casos prácticos.

Objetivos

Con la publicación de esta Tesis pretendemos abarcar varios objetivos. Por un lado, presentar al mundo académico universitario una serie de eventos de gran complejidad relacionadas con la operación y la seguridad de vuelo. Por ejemplo, problemas de toma de decisiones como son la cantidad de combustible de espera necesario para asumir demoras por congestión de tráfico aéreo en la fase de aproximación; o problemas de seguridad operacional, como las salidas por el final de pista durante el aterrizaje. Por otro lado, nos hemos planteado demostrar la utilidad de los métodos bayesianos en el análisis de riesgos, y la toma de decisiones en el ámbito de la seguridad operacional, en particular en la aviación comercial. Con ello, intentamos abrir nuevas vías de investigación a un mundo, como es el de la seguridad de vuelo, que ha evolucionado de forma considerable en la última década, y que por tanto, necesita nuevas herramientas y métodos de análisis. No podremos afrontar los futuros desafíos que, con toda seguridad, nos va a plantear la industria del transporte aéreo en los próximos años si nos seguimos apoyando en los mismos procedimientos y métodos de análisis que hasta ahora han resultado ser útiles.

Por otra parte, cuando hemos valorado diversas soluciones a los problemas planteados, no sólo desde un punto tecnológico, sino también de revisión de procedimientos, siempre hemos teniendo en cuenta que las medidas propuestas acarrean un coste económico para la organización y, por tanto, deben estar convenientemente justificadas. De esta forma, hemos querido destacar que, hoy en día, no es posible llevar a cabo una gestión eficiente de la seguridad de vuelo sin una profunda evaluación económica de las consecuencias de los eventos analizados y de las medidas mitigadoras propuestas. Un objetivo fundamental que todo analista de riesgos debe plantearse es el de demostrar a la organización que los costes necesarios para corregir situaciones potencialmente inseguras pueden ser rentables a corto o medio plazo. Para poder ilustrar estos conceptos, hemos aprovechado las posibilidades que la simulación ofrece a la hora de evaluar las probabilidades y consecuencias asociadas a los diferentes escenarios analizados.

Metodología

La Tesis está estructurada en cinco capítulos. En el Capítulo 1, presentamos una introdución general, donde exponemos el estado actual de la seguridad operacional en la industria del transporte aéreo. A continuación, discutimos ciertos conceptos significativos en la gestión de la seguridad operacional y en otros ámbitos que consideramos componentes críticos del proceso de gestión del riesgo, como son la comunicación y la percepción del riesgo. Posteriormente, ponemos de manifiesto la relevancia que tienen los aspectos económicos a la hora de afrontar una gestión eficiente de la seguridad. Por último, presentamos el marco metodológico general que posteriormente aplicaremos a los tres casos prácticos analizados: (1) el despliegue involuntario de las rampas durante la operación normal de la aeronave; (2) la determinación del combustible óptimo de espera por congestión de tráfico en la fase de aproximación; y (3) las salidas por el final de pista en el aterrizaje. Estos tres problemas constituyen la parte fundamental de la Tesis. Desde un punto de vista metodológico, el orden en el que se exponen es coherente, ya que de uno a otro no sólo aumenta la complejidad del problema, sino también las posibles consecuencias asociadas al evento, entre otras, las económicas. Siempre que ha sido posible, nuestros análisis se han basado en los datos disponibles, apoyándonos en la opinión de expertos cuando ha sido necesario, siempre bajo estrictos metódos de elicitación. Todos los cálculos y simulaciones han sido realizados con software libre, `R` y `WinBUGS`, con la ayuda puntual de `GeNIe` para el diseño del diagrama de influencia del Capítulo 4.

En el Capítulo 2 proponemos el primero de los casos prácticos. En él, mostramos cómo modelizar, evaluar y gestionar el riesgo asociado a un evento relativamente importante para las compañías aéreas: el despliegue involuntario de las rampas de seguridad durante la operación normal de la aeronave. Cada año, se producen numerosos sucesos involuntarios de este tipo, provocando una situación de riesgo para tripulaciones y personal de asistencia en tierra que en esos momentos se encuentren atendiendo la aeronave. Además, este evento lleva asociado unas pérdidas económicas significativas, especialmente en concepto de demoras para aquellas compañías con una estructura de distribución de pasaje en red, véase IATA (2005) y Cook and Tanner (2009). Después de una revisión de la literatura disponible, y con la información suministrada por expertos, procedemos a identificar los factores que podrían afectar potencialmente a este tipo de eventos. Como hemos señalado, este tipo de incidentes podría suponer un riesgo potencial para el personal que trabaja en torno a la aeronave. Sin embargo, al no disponer de datos históricos al respecto, decidimos concentrarnos en los aspectos económicos que, además, nos servirían posteriormente para convencer a la organización de la necesidad de adoptar ciertas medidas mitigadoras. Una vez más, basándonos en la bibliografía disponible e información aportada por expertos, identificamos los factores más relevantes y modelizamos el coste asociado a este tipo de eventos. A la hora de modelizar el coste por tiempo de demora nos apoyamos principalmente en el estudio de Cook and Tanner (2009). A partir de nuestro modelo, obtenemos la distibución predictiva de costes, que se demuestra está dominada por las demoras provocadas por el incidente. Para completar el análisis de riesgos combinamos, mediante simulación, la probabilidad y las consecuencias económicas de dichos sucesos. Finalmente, proponemos una serie de medidas mitigadoras estimando sus costes asociados.

En el Capítulo 3, presentamos un problema de decisión de gran importancia para las compañías aéreas, pues está directamente relacionado con la gestión del combustible. Actualmente, alrededor de un 30% de los costes directos de las aerolíneas se deben a esta partida. No se trata únicamente de un asunto relevante desde el punto de vista económico, sino también, desde el punto de vista de la seguridad operacional. En estos momentos y, por descontado en los próximos años, las aerolíneas tiene que gestionar el consumo de combustible de manera extremadamente eficiente para reducir su impacto en la cuenta de resultados y, por supuesto, evitar sucesos por "baja cantidad de combustible a bordo". Por otro lado, las demoras en aproximación por congestión de tráfico aéreo suponen no solo un consumo adicional para las compañías, sino también, costes añadidos, como por ejemplo, pérdidas de conexiones. Según Cook and Tanner (2011), en 2009 en Europa las pérdidas estimadas por demoras por congestión de tráfico aéreo supusieron un coste total de 1,250 millones de euros. En este contexto, proponemos un modelo para que los departamentos de operaciones puedan apoyar sus tomas de decisiones a la hora de determinar la cantidad de combustible de espera destinado a asumir, o no, la demoras en el aeropuerto de destino por congestión en aproximación. Se trata de un problema complejo. Por un lado, si la aeronave no tiene combustible suficiente para asumir el tiempo de espera, el comandante deberá decidir si procede al alternativo. Por otro lado, no se trata de cargar "cualquier cantidad de combustible" ya que, por el mero hecho de llevar este combustible extra a bordo, parte de él se consume por el exceso de peso, lo que se puede traducir en una importante penalización económica en términos anuales. A la hora de diseñar el modelo, el primer paso ha sido analizar y modelizar los costes económicos asociados, especialmente aquéllos relacionados con los pasajeros, para lo que nos hemos basado en el trabajo de Cook and Tanner (2011). En nuestro modelo de decisión hemos considerado varios escenarios, y hemos estructurado el problema con la ayuda de un árbol de decisión continuo. Para resolver el problema de la cantidad óptima adicional de combustible que se debe cargar para poder hacer frente a una eventual espera en el destino, maximizamos la utilidad esperada. Por razones de sencillez a la hora de implementar el modelo, hemos considerado como variable de decisión el tiempo de espera, en lugar del combustible adicional cargado, aunque ambas magnitudes son equivalentes desde un punto de vista operacional. Hemos aplicado nuestro modelo a dos casos prácticos, uno en el que hemos considerado una aeronave típica de largo radio, y otra de corto y medio radio. En ambos casos, hemos estimado el combustible de espera óptimo, considerando que el aterrizaje tiene lugar en diferentes franjas horarias. Por último, hemos dado un paso más en el estudio, en un aspecto que ha sido poco explorado en este tipo de trabajos, analizando cómo las distintas tendencias de aversión o afición al riesgo de las organizaciones influyen en la propuesta de combustible óptimo.

En el Capítulo 4, nos enfrentamos a uno de los problemas que más preocupa a la industria del transporte aéreo en materia de seguridad, las salidas por el final de pista en el aterrizaje, véase por ejemplo Rosenkrans (2012). Primero, hemos descrito el problema y hemos analizado los factores más relevantes recogidos en la bibliografía disponible de fabricantes, organizaciones y agencias dedicadas a la seguridad operacional, y de expertos en la materia. En especial, nos hemos basado en las recomendaciones para aterrizajes seguros (*Safe Landing Guidelines* en inglés) publicadas por la Fundación para la Seguridad Aérea (FSF, en sus siglas en inglés), véase Burin (2011). A partir de datos disponibles, y con la información anteriormente citada, hemos desarrollado un diagrama de influencia con la ayuda `GeNIe`, identificando las variables más significativas que posteriormente hemos implementado en nuestro modelo probabilístico. Para valorar el modelo, hemos propuesto tres pistas con condiciones operativas similares que hemos denominado Rwy-01, Rwy-02 y Rwy-03. Hemos analizado cada una de las variables identificadas como relevantes en el diagrama de influencia, modelizándolas según las particularidades de cada una, y deduciendo sus distribuciones predictivas. Hemos elegido como variable fundamental en nuestro estudio la longitud de pista remanente cuando la aeronave ha sido decelerada a 80 nudos. Con todo lo anterior, hemos usado un modelo probabilístico para estimar la probabilidad de que dicha longitud de pista sea menor que 2,000 pies (aproximadamente 610 metros) bajo distintos supuestos de interés. A la vista de las conclusiones obtenidas, validado con la opinión de expertos en operaciones de vuelo, proponemos algunas medidas correctoras o mitigadoras que se podrían implementar en aquellos casos en los que se detecta un riesgo excesivo de salida por el final de pista.

Por último, en el Capítulo 5 presentamos un resumen de las principales conclusiones a las que hemos llegado en cada uno de los sucesos analizados, así como una serie de temas abiertos que consideramos de gran interés para futuras investigaciones.

Resultados

A continuación destacamos los resultados más relevantes de cada uno de los casos analizados. En general, debemos enfatizar que ha quedado demostrada la utilidad de la aproximación bayesiana en al ámbito de la seguridad operacional, pues hemos propuesto modelos para la toma de decisiones que se han mostrado eficientes a la hora de reducir el número de sucesos no deseados y sus consecuencias potenciales.

En el primer caso práctico, estudiado en el Capítulo 2, el despliegue involuntario de rampas durante la normal operación del avión, una vez identificamos los factores contribuyentes, y partiendo de distribuciones a priori no informativas para los parámetros del modelo, hemos realizado un test de igualdad de proporciones basándonos en un modelo beta-binomial y Dirichlet-multinomial. Esto nos ha permitido llegar a una serie de conclusiones, siendo la más destacable (en contra de lo que en un principio se podía presuponer) que si consideramos tres días típicos de ocupación, la mayor proporción de despliegues involuntarios corresponde al primer día y no al último. Además, considerando "tres saltos" por día, también ocurre que la proporción de despliegues involuntarios es mayor en el primer salto que en el segundo o en el tercero. En otras palabras, y según la interpretación de este resultado por expertos en la materia, parece ser que la falta de conciencia situacional del primer día de trabajo y/o primer "salto" tiene una mayor influencia que la posible fatiga del último día y/o último "salto". También hemos identificamos la fase de vuelo y el personal que más veces aparecía involucrado en este tipo de situaciones. Esto nos ha permitido diseñar medidas mitigadoras más realistas y no basadas en supuestos apriorísticos. Concentrándonos en las consecuencias económicas del evento, hemos demostrado que esta aproximación es muy eficaz a la hora de convencer a la organización. Mediante la revisión del procedimiento de armado y desarmado de rampas, algo que apenas supone coste alguno para la compañía, el número de despliegues involuntarios se redujo durante el primer año en un 75%. Por último, y a modo de conclusión, podemos afirmar que existen otro tipo de riesgos operativos, especialmente en la misma fase de vuelo, que podrían beneficiarse de una aproximación similar a la aquí propuesta como, por ejemplo, sucesos en los que la aeronave resulta dañada por colisiones con el equipamiento auxiliar de tierra.

El segundo evento analizado, en el Capítulo 3, es un problema de decisión complejo, y se ha puesto de actualidad a raíz de que una compañía de bajo coste sufriese recientemente tres sucesos similares en el mismo día. La primera fuente de incertidumbre, la probabilidad de entrar en espera, la hemos modelizado a través de un modelo beta-binomial simple. Después de un análisis gráfico exploratorio de los datos, hemos adoptado para la variable tiempo de espera una mixtura de distribuciones gammas con cuatro componentes, siguiendo el modelo en Wiper et al. (2001). Para los tiempos de vuelo de desvío al alternativo hemos supuesto una distribución triangular. Finalmente, hemos llevado a cabo un proceso de optimización, asumiendo neutralidad al riesgo respecto a los costes, buscando minimizar el coste esperado. Para ilustrar nuestro modelo hemos considerado dos tipos diferentes de aeronaves que operan en el mismo aeropuerto de destino. Para el primer caso, una aeronave cuatrimotor de largo radio, hemos determinado los valores óptimos para cinco franjas horarias típicas, y los hemos comparado con las cargas estándar, demostrando un ahorro anual de más de 12,000 euros en la cuenta de combustible. Además, hemos simulado un año de operaciones en el destino considerado, para estimar el número de desvíos bajo esta nueva política de combustible de espera propuesta a partir de nuestro modelo, observando que la probabilidad de desvío al aeropuerto alternativo no aumenta en ningún caso. Como elemento adicional, y siendo conscientes de las consecuencias altamente negativas que supone un desvío al alternativo, en términos de imagen y pérdida de pasajeros, hemos repetido la simulación considerado los costes denominados "soft cost", ver Cook et al. (2012), obteniendo resultados similares. Hemos repetido el estudio para el segundo caso, considerando una aeronave bimotor de corto y medio radio, obteniendo resultados en la misma línea que los anteriores. Finalmente, hemos explorado las diversas políticas de aversión o propensión al riesgo de las distintas organizaciones. Hemos observado que aquellas compañías con aversión al riesgo (asimilables a las compañías "tradicionales", con un prestigio y número de clientes consolidado) siguen una postura más conservadora, es decir, suelen llevar cargas de combustible superiores a las propuestas bajo nuestro modelo. La situación contraria se da en aquellas compañías con políticas más agresivas en términos de reducción de costes, aún a costa de posibles incidentes o pérdida de imagen y/o clientes, que podrían estar más cerca del patrón de conducta de ciertas compañías low-cost. El problema aquí analizado pone de manifiesto la necesidad de implementar modelos que ayuden a la toma de decisiones, y que integren los diferentes departamentos de la compañía, con el objetivo de tener un conocimiento apropiado de los costes asociados a este tipo de eventos.

Por último, el caso práctico analizado en el Capítulo 4 estudia las salidas por el final de pista en el aterrizaje. Para ello, hemos desarrollado un modelo probabilístico donde se recogen las variables que consideramos más significativas en este tipo de sucesos: (1) la pista en cuestión; (2) el viento cruzado; (3) el viento en cola; (4) el criterio de desestabilización aceptado por la industria; (5) el tiempo en que se opera la reversa a máximo empuje; (6) el "autobrake"; (7) la diferencia entre la velocidad indicada (IAS) y la velocidad de aproximación que debería llevar el avión (Vapp); y (8) la altura a la que se sobrevuela el umbral. Según la FSF, el riesgo de accidente aumenta enormemente si la aeronave no se ha decelerado por debajo de los 80 nudos después de haber alcanzado los últimos 2,000 pies de pista remanente, véase Burin (2011). Ésta es la variable en la que nos hemos centrado para estudiar bajo qué circunstancias pueden aumentar las probabilidades de sufrir una salida por el final de la pista. Hemos considerado como un evento crítico el hecho de que esta variable tenga un valor inferior a los 2000 pies. Para evaluar la eficacia de nuestro modelo, hemos estudiado tres pistas con condiciones operativas similares, que hemos denominado respectivamente, Rwy-01, Rwy-02 y Rwy-03. Hemos utilizado la probabilidad de que la longitud de pista remanente a 80 nundos sea menor de 2,000 pies como indicador del riesgo de salida de pista en cada caso. Por otro lado, hemos analizado cada una de las ocho variables anteriormente mencionadas, modelizándolas según las particularidades de cada una, y deduciendo sus distribuciones predictivas. Los resultados más destacables a los que hemos llegado son: (1) Hemos observado que las variables que influyen de forma más significativa en la probabilidad de que la longitud de pista remanente a 80 nundos sea menor de 2,000 pies son el "autobrake" y la diferencia entre IAS y Vapp; (2) Considerando las tres pistas en conjunto, se ha estimado un alto riesgo de salida de pista en una de cada 5.000 aterrizajes, lo que equivale a menos de una operación al año, teniendo en cuenta las actuales condiciones de uso de las tres pistas; (3) Las condiciones de viento, tanto cruzado, como en cola, influyen en la desestabilización de la aproximación, pero no tanto como cabría esperar; (4) El modelo confirma, como se ha demostrado en multitud de análisis sobre este tipo de accidentes, que una aproximación desestabilizada aumenta el riesgo de salida de pista de forma evidente. En nuestro caso este fenómenos es especialmente significativo en la Rwy-02; (5) Finalmente, el modelo muestra una tendencia de los pilotos a "picar" por debajo de los últimos 100 pies con la intención de "aprovechar más la pista" (lo que se conoce en la jerga como "ducking under").

Conclusiones

En los últimos años la tasa de accidentes e incidentes a nivel mundial presenta un comportamiento relativamente estable, lo que podría deberse a que se ha alcanzado el equilibrio económico en materia de seguridad operacional. Por tanto, parece necesario abrir nuevas vías de investigación y desarrollar nuevas herramientas, ya que, para algunos autores, la actual aproximación sobre gestión del riesgo adoptada por ICAO es simplista y está poco fundamentada desde el punto de vista científico. Además, los nuevos desarrollos tecnológicos han empezado a provocar nuevos tipos de incidentes y accidentes hasta ahora desconocidos. En esta Tesis, y con la intención de ayudar a cubrir en parte los vacíos metodológicos en este este tipo de eventos, proponemos una aproximación bayesiana al análisis de riesgos inexistente en el ámbito de la aviación comercial.

Por otro lado, el concepto de seguridad operacional ha evolucionado últimamente hacia la gestión del riesgo. Por tanto, debe destacarse la relevancia que para una gestión eficiente de la seguridad tienen los aspectos económicos. En este sentido, a la hora de estimar la validez y eficacia de las medidas mitigadoras propuestas es necesario hacer un análisis económico profundo de los costes que éstas pueden suponer para la organización. En concreto, es especialmente complejo modelizar ciertos tipos de costes, como aquéllos relacionados con la pérdida de imagen u otros relacionados con los costes que afectan laos pasajeros. Por último, cabe destacar que en los últimos años el factor humano en aviación ha cobrado gran relevancia. Los expertos en seguridad aérea suelen afirmar con rotundidad que en los incidentes y accidentes aéreos el factor humano es el principal responsable en aproximadamente el 70% de los casos. Sin embargo, podríamos afirmar, sin temor a equivocarnos, que la "cifra exacta rondaría el 100%". No existe en aviación ningún sistema en el que no esté presente, de forma directa o indirecta, el factor humano. Aunque existe una amplia literatura sobre este tema, aún no se han desarrollado modelos apropiados que puedan ser utilizados para estimar el riesgo en diferentes tipos de incidentes o accidentes. En relación con este aspecto, la percepción que del riesgo tiene el ser humano es un campo que aún no ha sido suficientemente estudiado ni entendido.

Preface

The combination of the likelihood of a negative outcome and its consequences leads to the notion of risk. If we were completely certain about the future behavior of a system, risk would not be present. On the other hand, real systems are always subject to some kind of uncertainty, which can be modeled mathematically, in a first approach, with the aid of probability distributions. But recent years have seen a significant advance in the development of more sophisticated tools, as the use of risk analysis in several fields, e.g. in the nuclear sector.

However, in the domain of commercial aviation (the framework for this PhD Thesis), this has not yet been fully integrated within the operations management structures. In the aerospace sector, systematic concern about the risk assessment methodology began after the fire of the Apollo test AS-204 on January 27th, 1967, in which three astronauts were killed. This event involved considerable loss of public support and huge amount of money in additional costs, see Bedford and Cooke (2007). Nowadays, risk analysis has already proven successful in general decision-making processes.

We have focused in this PhD Thesis on operational risks of complex safety-critical systems, in which unlikely undesired events during operation can lead to catastrophic losses (Lp/Hc events). Nevertheless, at present, risk analysis in air transport domain has adopted simplistic and poor scientific methods. Furthermore, risk matrices are being used as the single communication tool. But risk matrices have several inherent characteristics, as ambiguous inputs and outputs, see Cox (2008), which call into question their suitability to manage risk. According to Haimes (2009), given that risk cannot be managed unless it is properly assessed, and that the best assessment process is accomplished through modeling, the modeling process should become an imperative step in the systematic assessment and management of risk. Moreover, it is critical that the inference methods used within these models are robust. In this context, the current naive approach could become the safety risk analysis process in a “paper safe”. In this PhD Thesis, we have intended to take a step forward.

This PhD Thesis is composed of five chapters. Three of them present a Bayesian approach to commercial aviation risk management, illustrated with three relevant case studies under conditions of risk and uncertainty in the industry. The complexity of the proposed models is increased in each case study. To implement and evaluate our models, we have used Markov Chain Monte Carlo (MCMC) methods, in open source software (R and WinBUGS).

In Chapter 1, we present the basic operational safety and risk concepts in civil aviation. We also deal with the issues of risk communication and perception, which are relatively new fields although critical components of the whole safety risk management process. As it is well known, safety management is currently viewed as just another organizational process that allows aviation organizations to achieve their business objectives. For this reason, we have provided an overview of some economic considerations of aviation safety. Finally, we review the framework that we shall use in our case studies.

In Chapter 2, we deal with a relatively important incident in airlines operations: the unintended deployment of emergency slides under normal operation. This type of events occur every year around the world, becoming a safety issue for passengers, crew and ground staff, also with relevant financial implications. Upon discussion with experts and after reviewing the existing literature, we have identified several factors affecting this kind of events. Under noninformative priors, we have performed a test of equal proportions in relation with those factors, based on beta-binomial or Dirichlet-multinomial models. Although unintentional slide deployment could potentially cause serious injuries, we have focused on its economic impacts, mainly due to the lack of reported data concerning injuries. We have combined, through simulation, our likelihood and consequence models to complete the risk assessment. Afterwards, we have described several relevant countermeasures aimed at mitigating this hazard to an acceptable level. We have analyzed not only technical solutions but also procedure revisions, as mitigation measures need to be practical and cost effective to be accepted by aviation industry. Finally, we have proposed to translate our results into a nontechnical language, as part of the communication risk process, so that decision-makers can understand them and incorporate them into their decisions.

Chapter 3 focuses on a decision analysis model to support the airline companies how much extra fuel to carry on for holding at destination. Currently, the air transport industry fuel bill accounts for around 30% of annual operating costs. One of the main reason for holding is traffic congestion at approach phase. It is standard to fuel aircrafts with an estimated additional fuel quantity if there is information about delays at airport destination, without modeling and assessing potential side costs. Such costs may be particularly significant for those airlines with hub-and-spoke distribution models rather than point-to-point route network. To model the problem, and in order to reduce complexity, we have used the holding time as our decision variable. We have structured the problem with the aid of a continuous decision tree. We have illustrated the problem using two different scenarios: one for short-medium range aircrafts, and the other one for long range aircraft types. Assuming risk neutrality in costs within the incumbent airline, we explore the implication of risk aversion on the fueling decision.

In Chapter 4, we deal with runway excursions at landing, an event considered as a major threat to aviation safety as they account for approximately 25% of all incidents and accidents in air transport, and 96% of all runway accidents. While the occurrence rate of these events is very low, the entailed consequences may be very severe. Again, upon reviewing the existing literature, and gathering information from manufacturers, operators and safety agencies as well as experts' opinion and data available, we have analyzed the main contributing factors. Based on these factors, and in order to visualize the most relevant ones, we have designed a mind map, building an associated probabilistic influence diagram. From the graphical model, we have also defined a probabilistic model with a key variable based on a FSF study, see Burin (2011). A case study is used in order to illustrate in detail our methodology. At the end, we highlight some interesting results relating to the influence of the model variables in the day-to-day landing distance performance.

Finally, in Chapter 5, we present the remarking conclusions regarding the issues discussed throughout this PhD Thesis, and we also discuss some topics which could be worth considering for future research.

As a concluding remark, and at the light of the results and conclusions obtained throughout this PhD Thesis, it is noteworthy to emphasize that, not only it is evident that safety thinking has experienced a significant evolution in the last years, but also, that new technologies in air transport have raised new incidents or accidents types which do not fit the traditional causation model. New hazards will require new ideas. Upon review of the existing literature, we have acknowledged a lack of studies in the field of aviation safety risk in the academic world. With this PhD Thesis, we try to encourage further research into this field and we hope to have contributed to implement new ideas and mathematical tools in the field of risk analysis and safety decision-making.

Chapter 1
Introduction

1.1 Introduction

Aviation has been dealing with preventing accidents since the earliest days of flying, when the Wright brothers made the first heavier than air flight in 1903. From 1945 to the present day, the International Civil Aviation Organization (ICAO) has been publishing accident rates involving passenger fatalities (excluding acts of unlawful interference with civil aviation) for scheduled commercial transport operations. Thenceforth, statistics support the fact that aviation is the safest transportation mode available. In February 2013, IATA announced that the 2012 global accident rate for Western-built jets has been the lowest in aviation history, see IATA (2013a). The rate, measured in hull losses per million flights of Western-built jets, was 0.20, the equivalent of one accident every 5 million flights. This represented a 46% improvement over 2011, when the accident rate was 0.37, or one accident for every 2.7 million flights. Unfortunately, as shown in Figure 1.1, accident rates for scheduled operations differ significantly across world regions, see EASA (2012a).

In Europe, 2010 was the first year in which no fatal accident in commercial air transport operations for helicopters and airplanes occurred, see EASA (2011). In 2011, there was a single fatal accident in which 6 persons on board received fatal injuries, see EASA (2012a). Such high safety level has been possible as a result of different factors for controlling and minimizing aviation's safety hazards. For instance, the Second World War was a significant event in aviation safety, as aircraft technology advanced rapidly and it was transferred to commercial aviation. Figure 1.2 shows that the evolution of the jet engine through the 1960s resulted in an accident rate that decreased exponentially, reaching a level that has been maintained over the following four decades.

Based on the number of passenger fatalities per 100 million passenger miles

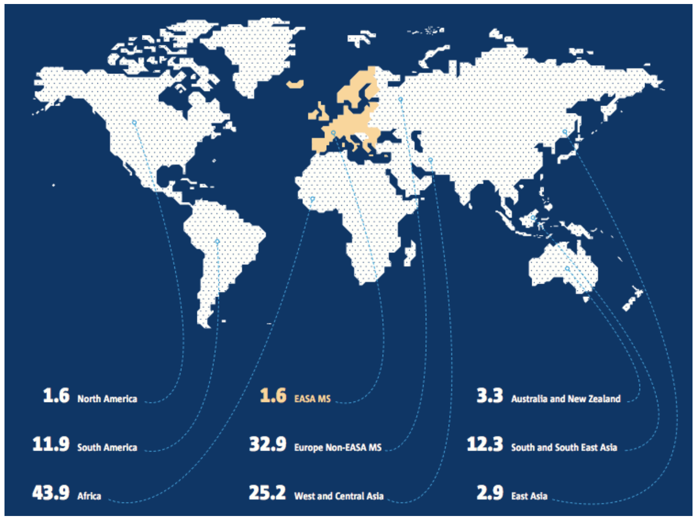


Figure 1.1: Rate of fatal accidents per 10 million flights (2002 – 2011), scheduled passenger and cargo operations. Source: EASA (2012a).

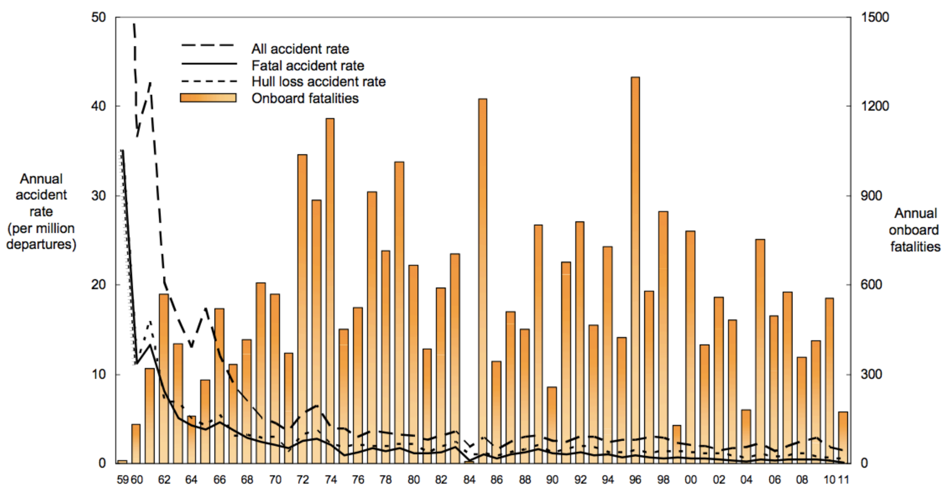
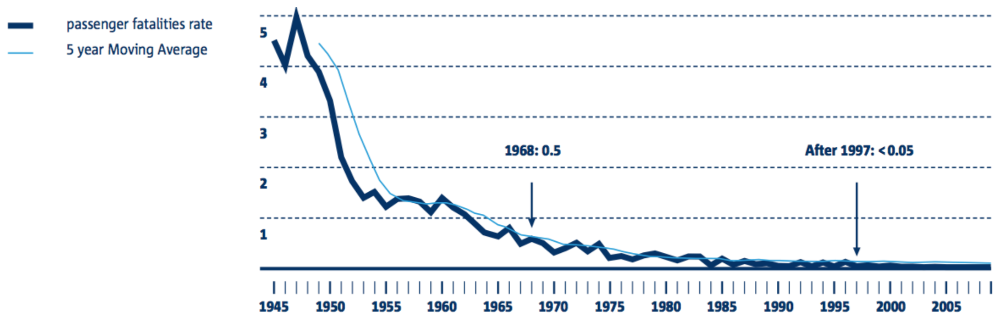
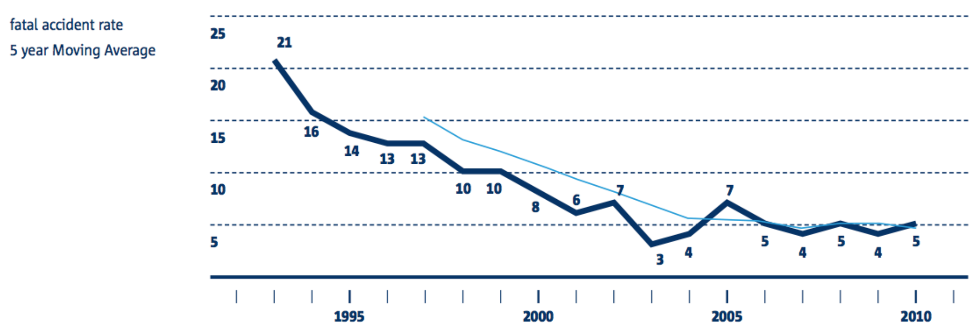


Figure 1.2: Accident rates and onboard fatalities worldwide commercial jet fleet 1959 – 2011. Source: Boeing (2012)

flown, Figure 1.3 shows that it took some 20 years (1948 to 1968) to achieve the first 10-fold improvement from 5 to 0.5. Another 10-fold improvement was reached in 1997, almost 30 years later, when the rate dropped below 0.05. The accident rate in Figure 1.3 (a) seems to have been flat over recent years up to 2003, but this is just the result of the scale used to reflect the high rates in the late 1940s, see Figure 1.3 (b). However, since 2004, the accident rate has been relatively steady. The rate of fatal accidents has not improved significantly, averaging between 4 and 5 fatal accidents per 10 million flights. This could be due to the fact that aviation safety has reached an economic equilibrium, a point in which the benefits of safety are approximately equal to the costs, see Vasigh et al. (2008), who consider that the economic equilibrium could have been reached in the 1980s.



(a) 1945 to 2009



(b) 1992 to 2010

Figure 1.3: Global passenger fatalities per 100 million passenger miles in scheduled commercial air transport operations, excluding acts of unlawful interference. Source: EASA (2011).

Commercial air transport operations include the transportation of passengers, cargo and mail. Accidents concerned involve aircrafts with a certificated Maximum Take-Off Mass (MTOM) over 2,250 kg. States are required, according to ICAO (2010) Annex 13 to the Convention on International Civil Aviation to report accidents to that organism. Accidents and fatal accidents are identified as such using the following definitions:

- Accident. An occurrence associated with the operation of an aircraft which takes place between the time any person boards the aircraft, with the intention of flying, until such time in which all such persons have disembarked, in which:

- a person is fatally or seriously injured as a result of: being in the aircraft, or direct contact with any part of the aircraft, including parts which have become detached from the aircraft, or direct exposure to jet blast, except when the injuries are from natural causes, self-inflicted or inflicted by other persons, or when the injuries are to stowaways hiding outside the areas normally available to the passengers and crew; or
- the aircraft sustains damage or structural failure which: adversely affects the structural strength, performance or flight characteristics of the aircraft, and would normally require major repair or replacement of the affected component, except for engine failure or damage, when the damage is limited to the engine, its cowlings or accessories; or for damage limited to propellers, wing tips, antennas, tires, brakes, fairings, small dents or puncture holes in the aircraft skin; or
- the aircraft is missing or is completely inaccessible.

• Incident. An occurrence, other than an accident, associated with the operation of an aircraft which affects or could affect the safety of operation.

According to these definitions, ICAO (2006b) emphasizes that safety industrial research in 1969 established what is known as the 1:600, see the relationship illustrated in Figure 1.4.

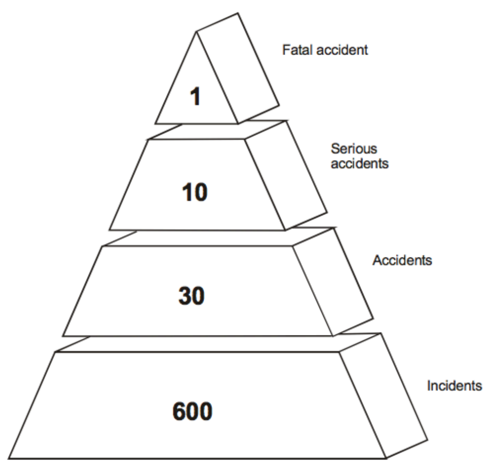


Figure 1.4: 1:600 Rule. Source: ICAO (2006b)

The ICAO definitions use “occurrence” to indicate an accident or incident. From the safety operational management point of view, there is a danger in concentrating on the difference between accidents and incidents, using definitions sometimes arbitrary and limiting. The difference may simply be an element of chance that under slightly difference circumstances or latent unsafe conditions could have been classified as an accident, see ICAO (2006b). Figure 1.5 illustrates the current thinking of accident causation.

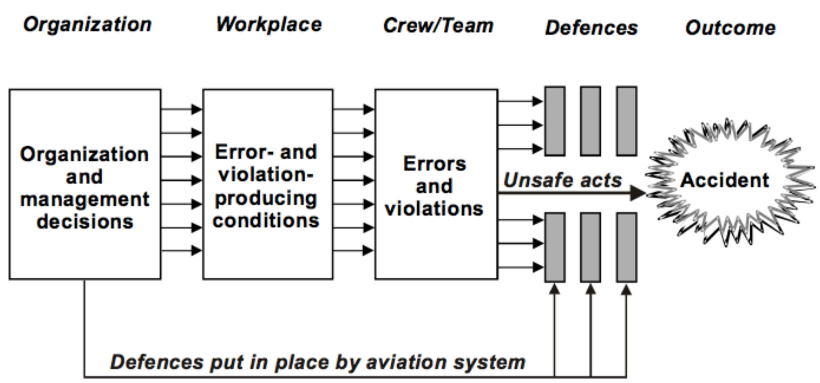
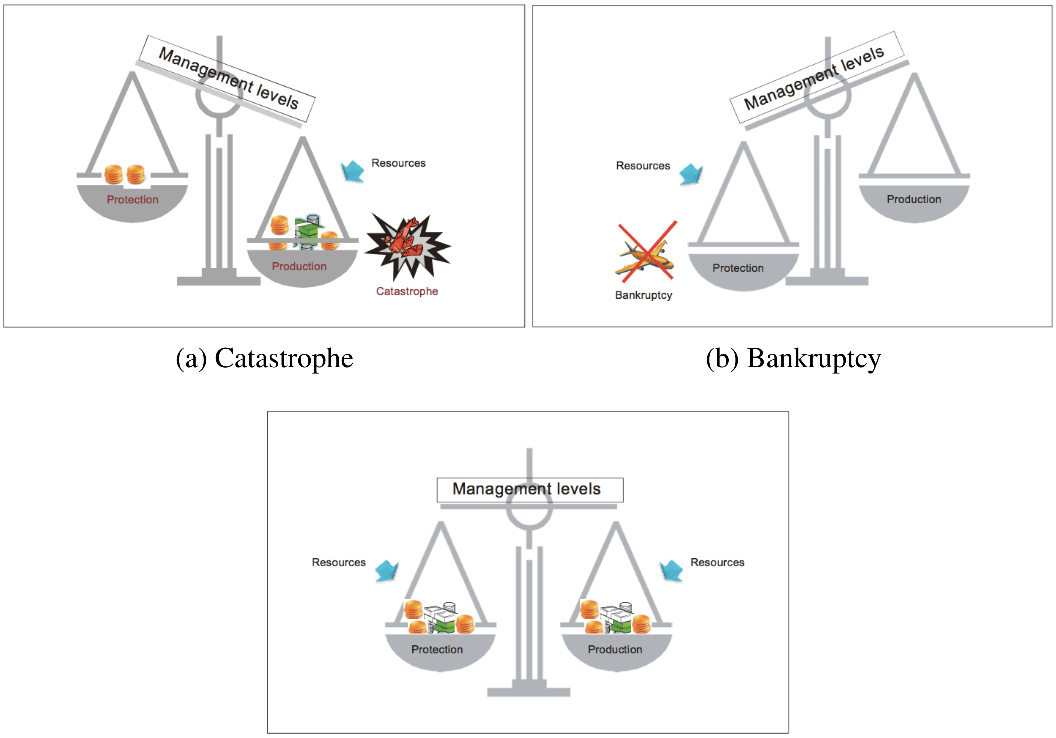


Figure 1.5: Accident causation. Source: ICAO (2009)

While the elimination of accidents and serious incidents would be desirable, a hundred per cent safety rate is an unachievable goal. Failures and errors will occur, in spite of the best efforts to avoid them. No human activity or human-made system can be guaranteed to be absolutely safe, i.e. risk free, see ICAO (2006b). Furthermore, in common usage, the term "safety" is often used as an absolute value, that is, one is either safe or unsafe. However, safety is never absolute, since there is always a probability of accident. Thus, safety depends on the given situation and the risks inherent to that situation. Nevertheless, many people claim that safety should be maximized, regardless of the cost and the fact that the available resources are finite, see Vasigh et al. (2008). Although expressions like "safety must be preserved at any price" are commonly used, since a few years ago, safety is increasingly viewed as a risk management issue, and it has been judged within the economic context of a cost-benefit analysis, where increases in safety are optimal only when the safety benefits justify the costs. The management dilemma can be characterized as the conflict between two goals; production and safety goals, see Figure 1.6.

Over the last years, the aviation industry has started to change the concept of safety, from a relative contemporary perspective (i.e., risk management) rather than the absolute long-established traditional approach (i.e., zero accidents or freedom from hazards). ICAO admits that "safety is the state in which the risk of harm to persons or property damage is reduced to, and maintained at or below, an acceptable level through a continuing process of hazard identification and risk management", see ICAO (2006b). This new point of view is supported by ICAO through the regulatory framework of the Safety Management System (SMS). A Safety Management



(a) Catastrophe (b) Bankruptcy

(c) Equilibrium

Figure 1.6: The management dilemma. Source: ICAO (2009).

Manual has been provided to the States as a guidance to support the implementation of SMS by service providers, and for the development of a State Safety Programme (SSP), in accordance with the International Standards and Recommended Practices (SARPs), see ICAO (2009).

Similarly, the process known as risk management is defined as: "the identification, analysis and elimination (and/or mitigation to an acceptable or tolerable level) of those hazards, as well as the subsequent risks, that threaten the viability of an organization". ICAO, as other government organizations or agencies, like the Federal Aviation Administration (FAA), also describes risk as a measure of the expected losses which can be caused by an undesired event, multiplied by the probability of the event occurring;

$$Risk = Severity \times Likelihood$$

Thus, as safety as risk management seems to prove, aviation safety thinking has experienced, in retrospect, a significant evolution over the last fifty years, see ICAO (2009). Figure 1.7 shows this evolution, with the 1990s signaling the beginning of the "organizational era", when safety began to be viewed from a systematic perspective, to encompass organizational, human and technical factors, see ICAO (2009).

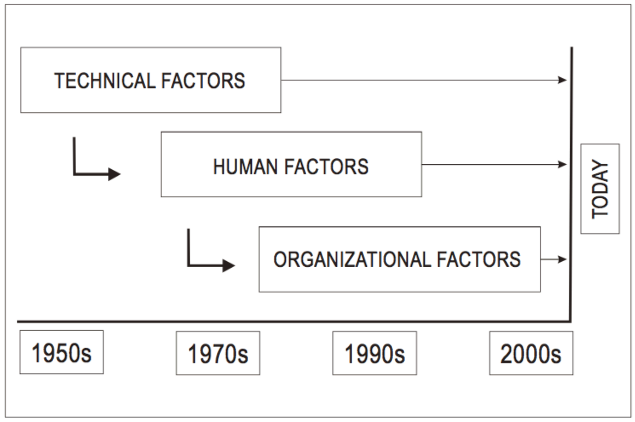


Figure 1.7: The evolution of safety thinking. Source: ICAO (2009)

One fact that leads strong support to the more contemporary system approach is that similar situations keep provoking the same kinds of unsafe acts in different people. These recurrences indicate that a substantial part of the problem is rooted in error-provoking situations rather than in error-prone people. A primary objective of event reporting systems is to identify such "error traps". Eliminating then must become a priority task for error management systems, see Reason (2008).

1.2 Basic operational safety and risk management concepts in aviation

1.2.1 Operational safety

Safety management must be a systematic closed loop process to hazard identification and risk management, aiming at minimizing the loss of human life, property damage and/or financial and societal losses. Sometimes, it is difficult to establish or define safety boundaries, and therefore, according to financial or economic resources, companies must determine which issues must be investigated under the safety point of view.

As it has been emphasized before, the concept of operational safety in aviation has had different connotations depending on the perspective. However, they all have shared an underlying idea; the possibility of absolute control. As ICAO notices, in its beginning, commercial aviation was a loosely regulated activity, with an underdeveloped technology and an insufficient understanding of the hazards associated with aviation operations. On those days, accident investigation was the main way of prevention. By the 1950s, technological improvements led aviation to become one of the safest industries, as well as, one of the most heavily regulated. This operational safety approach was quite effective in identifying "what", "who" and "when" an incident or accident happened, but it was less effective in disclosing "why" and "how", see ICAO (2009).

Until the 1970s, safety concerns were mostly related with technical factors. From these years, safety began to consider human factors. It was not until the early 1990s that it was first acknowledged the fact that the operational context could influence human performance. At this time, safety began to be viewed from a systematic perspective to encompass technical, human and organizational factors, see Figure 1.8.

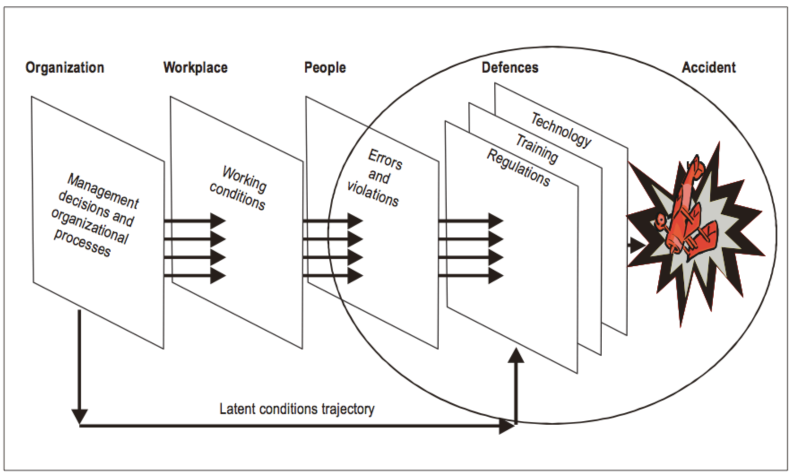


Figure 1.8: Reason model of accident causation. Source: ICAO (2009)

Reason (2008) developed a model in which the concept of organizational accident was explained. In Reason's model, all incidents or accidents are due to a combination of both active and latent conditions. Active failures are actions or inactions, including errors and violations. Latent conditions become evident once the defences of the system have been breached. As we commented, aviation had an accident rate of less than one fatal accident per million departures for the last decade. However,as ICAO (2009) established, it is a statistical fact that, in aviation, millions of operational errors are made on a daily basis before a major safety breakdown occurs. This means that the control of operational errors takes place on a daily basis through the effective performance of the aviation system defences.

The aviation operational environment is very complex, and its performance involves complex relationships among their many components. A conceptual tool for the analysis of the components and features of operational contexts and their interactions with people is modeled through the *SHELL model*, see Figure 1.9.

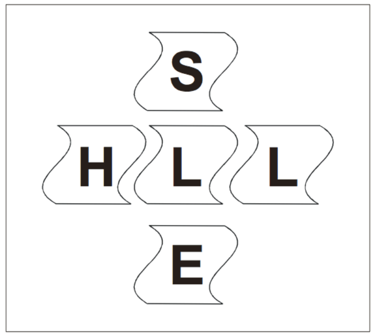
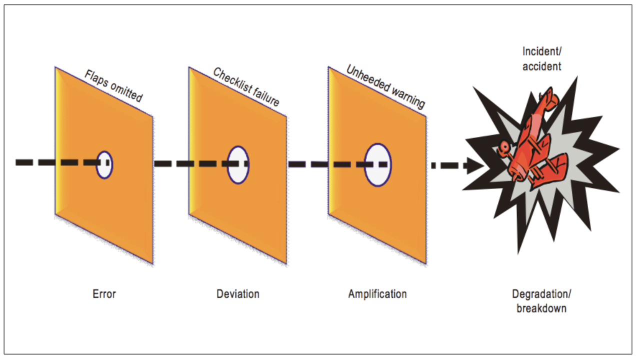


Figure 1.9: SHELL model. Source ICAO (2009)

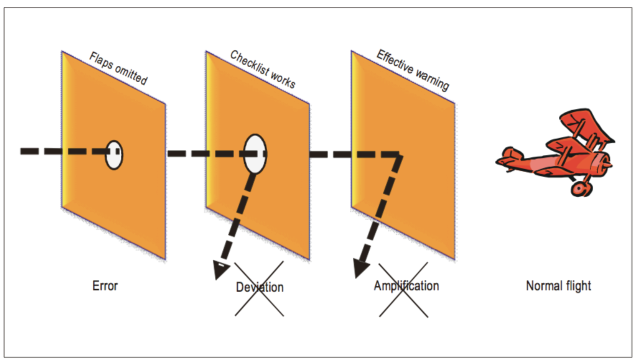
As ICAO (2009) highlights, the SHELL model is particularly useful in visualizing the interfaces between the various components of the aviation system, including:

- Liveware-Hardware (L-H). Interface between the physical work environment and technologies
- Liveware-Software (L-S). Interface between the human and the supporting systems found at workplace, such as regulations, manuals, checklists, publications, standard operating procedures (SOPs) and computer software.
- Liveware-Liveware (L-L). Interface between the human and other persons at the workplace, as others members of flight crews, air traffic controllers, aircraft maintenance engineers, staff/management, etc.
- Liveware-Environment (L-E). Interface between the human and both the internal (temperature, ambient light, noise, vibration, air quality, etc.) and external environments (visibility, turbulence, etc.).

ICAO used an operational scenario example to explain the asymmetry between operational errors and their consequences. This scenario was very similar to the accident occurred when a MD-82 passenger plane was destroyed when it crashed while taking-off from Madrid-Barajas Airport, on August 20th 2008, see CIAIAC (2011). 154 occupants were killed, including all six crew members, and 18 were seriously injured. The "Comisión de Investigación de Accidentes e Incidentes de Aviación Civil" (CIAIAC) determined that the accident occurred because the crew lost control of the aircraft as a result of a stall immediately after take-off, when the flaps/slats were not deployed, following a series of failures and omissions, and with the absence of a warning to the flight crew in the cockpit about the incorrect setting. The Take-Off Warning System (TOWS) did not work properly and, therefore, did not alert the crew, see Figure 1.10.



(a) Once in a million flights



(b) On almost every flights

Figure 1.10: Asymmetry between operational errors and the immediacy of their consequences. Source: ICAO (2009).

Sometimes, an operational error penetrates the first layer of defences, Standard Operational Procedures (SOP). Usually, there are no immediate consequences. The operational error just remains in the system, in latency. If further opportunities to recover from the consequences of the operational error are missed, the system is in a state of deviation, but this undesired state magnifies with time. After breaching a considerable number of built-in system defenses, the operational error develops its full damaging potential and the system experiences a catastrophic breakdown. The more built-in defenses (layers) of containment the system includes, and the more efficient their performances are, the greater the possibilities of controlling the consequences are. Notice that the reverse is true, see ICAO (2009).

We should distinguish between errors and violations. As defined by ICAO

(2009), the fundamental difference lies in intent. While an error is unintentional, a violation is a deliberate act. People committing operational errors are trying to do the right thing. People committing violations know that they are engaging in a behavior that involves a deviation from established procedures or practices.

The predominant mode of treating human contributions to the reliability of complex well-defined systems is to consider humans as a hazards; i.e., a system component whose unsafe acts are involved in most catastrophic breakdowns. However, there is another perspective, which has been studied relatively little in its own right, and which considers humans as a system element whose adaptive behavior brings troubled systems back from the brink of disaster on a significant number of occasions, see Reason (2008). As this author establishes, this could be due to the fact that most observations of people in high-risk systems emerge from well-documented accident investigations, and it is inevitable that we should know far more about human caused hazards.

Currently, safety management in aviation is considered another organizational process. Resource allocation must be balanced to ensure that the company is protected while it produces. However, the history of aviation shows that an effective resolution of the safety dilemma, see Figure 1.6, has not been commonplace, see ICAO (2009). What accident investigations show is a tendency for organizations to drift into balance in the allocation of resources in which safety is usually the loser. In these organizations, it is a matter of time that such decision making style will eventually lead to a catastrophe.

1.2.2 Hazard

Hazard identification and safety risk management are the core processes involved in safety management, see ICAO (2009). How these hazards are identified will depend on the resources and procedures at each particular organization.

As established by ICAO since 2006, see ICAO (2006b) and update ICAO (2009), a hazard is defined as a condition or an object with the potential to cause injuries to personnel, damage to equipment or structures, loss of material, or reduction of ability to perform a prescribed function. It should be noticed that hazards are not necessarily damaging or negative components of a system. Only when they interact with system operations, their damaging potential may become a safety concern. Sometimes there is a tendency to confuse hazards with their consequences. ICAO grouped hazards into three generic families;

- Natural hazards. These are consequences of the environment within which operations related to the provision of services take place, e.g. adverse weather conditions, geographical conditions, etc.

- Technical hazards, from aircraft systems or components.
- Economic hazards, that are the consequences of the socio-political environment as recession periods.

Figure 1.11 depicts a process for hazard identification suggested by ICAO (2009).

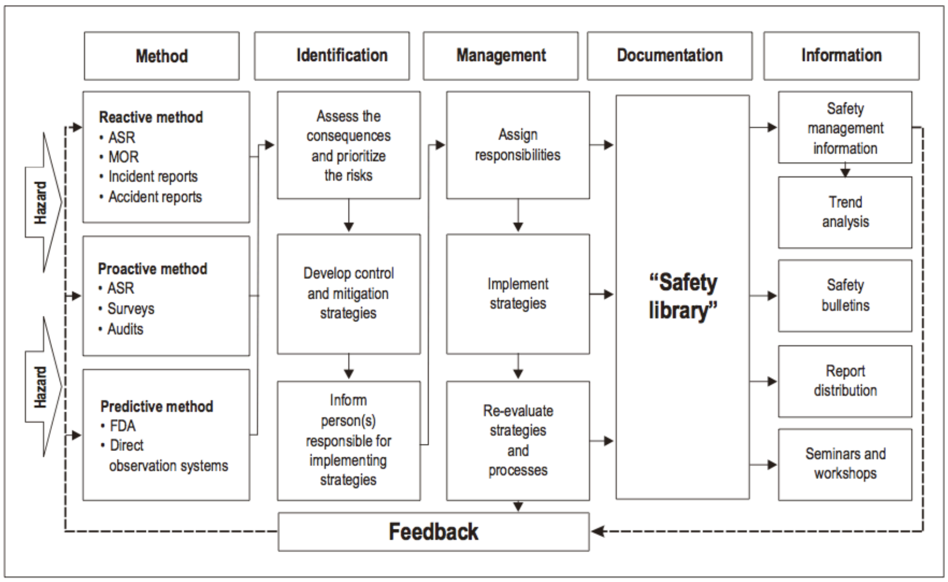


Figure 1.11: Documentation of hazards. Source: ICAO (2009)

1.2.3 Risk

Safety risk management is the other core activity that supports safety management. It is a basic management axiom that one cannot manage what one cannot measure. Therefore, it is essential to somehow measure the seriousness of the consequences of hazards. This is the essential contribution of safety risk management to the safety management process, see ICAO (2009). Beside this, and as a remarkable fact, risk can never be zero by increasing mitigation measures, as hazards will always be present.

In the aerospace sector, a systematic concern with the risk assessment methodology began after the fire of the Apollo test AS-204 on January 27th, 1967, in which three astronauts were killed. This event involved considerable loss of public support, costed the National Aeronautics and Space Administration (NASA) salaries and expenses for 1500 people involved in the subsequent investigation, and ran up to USD 410 millions in additional costs. Prior to the Apollo accident, the NASA relied on its contractors to apply "good engineering practices" to provide quality assurance and control, see Bedford and Cooke (2007). Since the shuttle accident, NASA has instituted programs of quantitative risk analysis to support safety during the design and operation phases of manned space travel. The goals and sizes of risk analyses vary widely. The nuclear sector has made the largest commitments of resources in this area, especially in the probabilistic risk analysis field. However, in the aerospace sector, the methods have not yet been fully integrated into the existing design and operations management structures, see Bedford and Cooke (2007).

Not all risks can be eliminated, nor are all conceivable risk mitigation measures economically feasible. The risks and costs inherent in aviation needs a rational process for decision-making, see ICAO (2006b). There are several definitions of the process known as risk management, but all have as a common line, the fact that it is a combination of undesirable consequences of accident scenarios. The probability of these scenarios, i.e., risk assessment, is the process of measuring risk and developing strategies to manage it. These strategies usually include reducing the negative effect of the risk, see Stolzer et al. (2008). Determining risk generally amounts to answering the following questions, see Stamatelatos et al. (2002):

- What can go wrong? The answer to this question is a set of accident scenarios.
- How likely are they? This question requires the evaluation of the probabilities of these scenarios.
- What are the consequences? To address this issues we need to estimate their consequences.

Risk management, an integral component of safety management that involves a logical process of objective analysis, see Figure 1.12, must facilitate the balancing between assessed risks and mitigation measures.

The risk management process illustrated in Figure 1.13 must be applied under a continuous approach, providing a disciplined and documented management for proactive decision making, see Stamatelatos et al. (2002), in order to:

- Assess continuously what could go wrong (risks).
- Determine which risks are important to deal with.
- Implement strategies to deal with such risks.

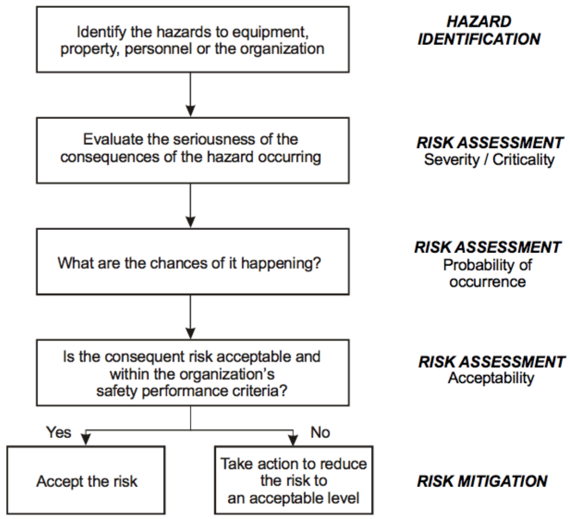


Figure 1.12: Safety risk management process. Source: ICAO (2006b)

Figure 1.13: Risk management process. Source: Stamatelatos et al. (2002)

- Ensure effectiveness of the implemented strategies.

Risk analysis comprises three essential subprocesses:

1. Hazard identification. As in any analytical process, the problem (hazard) is defined in first place. However, this is not always easy, as people from different backgrounds and experience will likely view the same evidence from different perspectives. As established by ICAO (2006b), given that a hazard involves any situation or condition that has the potential to cause adverse consequences, the scope for hazards in aviation is wide. Some examples are:

    - Design factors.

- Procedures and operating practices such as manuals and checklists.
- Communications, which may be related with equipments, terminology or different mother language between pilots-controllers.
- Organizational factors, such as operating pressures and the corporate safety culture.

Safety reporting systems should include hazards, i.e. unsafe conditions that have not yet caused incidents or accidents. To support a reporting culture, the organization must cultivate the willingness of its members to contribute to the organization's understanding of its operation. Since some of the most valuable reports involve self-disclosure of mistakes, the organization must make the commitment to act in a non-punitive manner when those mistakes are not the result of careless or reckless behavior, see Stolzer et al. (2008).

2. Risk assessment. Assessment of the hazard involves three considerations:

- Probability of the hazard precipitating an unsafe event.
- Severity of the potential adverse consequences that will govern the degree of urgency attached to the safety action required.
- The rate of exposure to the hazards as the probability of adverse consequences becomes greater through increased exposure to the unsafe conditions.

A safety assessment should be undertaken prior to the implementation of any major change potentially affecting the safety of operations, in order to demonstrate that the changes meet an acceptable safety level. Figure 1.14 presents the flow diagram of the safety assessment process stated by ICAO in its Safety Management Manual (SMM), see ICAO (2006b).

3. Risk management. The SMM published by ICAO states that when a risk has been found to be undesirable or unacceptable, control measures need to be introduced considering that "the higher the risk, the greater the urgency". The level of risk can be lowered by reducing its severity, its likelihood or by reducing the exposure to that risk. The optimal solution will depend on the circumstances, but risk has to be managed to a level known as "as low as reasonably practicable" (ALARP), meaning in practice, that the risk mitigation measures must be examined from perspectives such as:

- Effectiveness. Will it reduce or eliminate the identified risks?
- Cost/benefit. Do the perceived benefits of the option outweigh the costs?

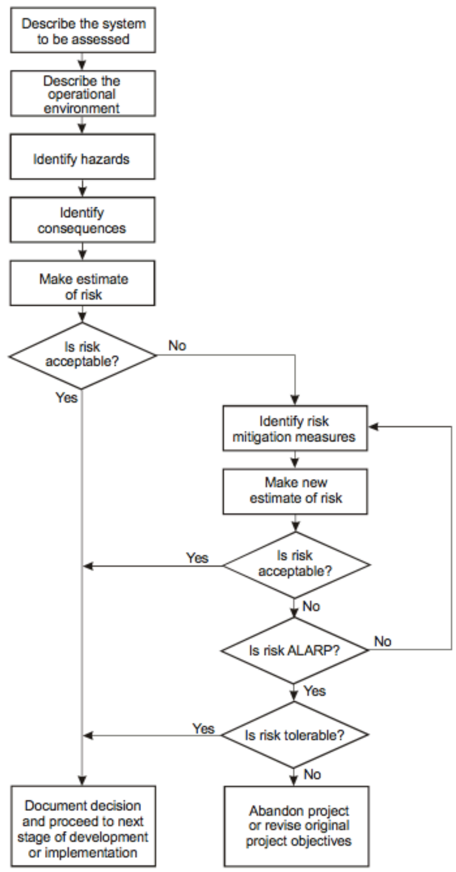


Figure 1.14: Safety assessment process. Source: ICAO (2006b)

- Practicality. Is it doable and appropriate in terms of available technology, financial and administrative feasibility, governing legislation and regulations, political will, etc?
- Challenge. Can the risk mitigation measure withstand critical scrutiny from all employees, managers, state administrations, etc?
- Acceptability. How much buy-in or resistance can be expected?
- Enforceability. If new rules (SOPs, regulations, etc.) are implemented, are they enforceable?
- Durability. Will the measure withstand the test of time?
- Residual risks. After the risk mitigation measure is implemented, what will the residual risks relative to the original hazard be?
- New problems. What new problems or new risks will be introduced by the proposed change?

Therefore, risk of harm or damage must be limited to an acceptable level. Defining acceptable and unacceptable risks is an important issue for cost-effective safety management. According to ICAO (2006b), the experience in other industries and from the aircraft accident investigations have emphasized the importance of managing safety in the following way:

- Systematic, safety management activities will be conducted in accordance with a predetermined plan and applied in a consistent manner throughout the organization.
- Proactive, this approach emphasizes prevention through the identification of hazards. It introduces risk mitigation measures before the risk-bearing event occurs.
- Explicit, safety management activities should be documented, visible and performed independently from other management activities.

To determine an "acceptable level of safety" it is necessary to consider such factors as the level of risk that applies, the cost/benefits of improvements to the system and/or public expectations on the safety of the aviation industry. The Tolerability of Risk (TOR) triangle, see Figure 1.15, has been developed to help to communicate risk acceptability.

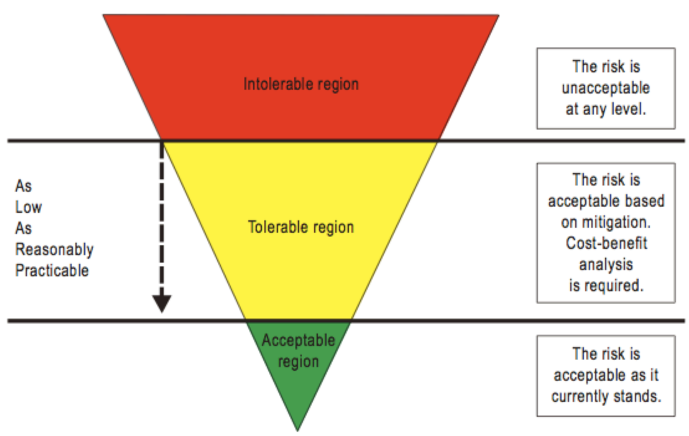


Figure 1.15: TOR triangle. Source: ICAO (2009)

As we have mentioned before, the acronym ALARP is used to describe a risk that has been reduced to a level that is as low as reasonably practicable. This means that any further risk reduction is, either impracticable, or grossly outweighed by the cost. It must be noticed that, even if a risk is accepted, this does not mean that it has been eliminated, as some level of risk remains, but it is sufficiently low that it is outweighed by the benefits.

According to ICAO (2006b), the safety management process should involve a continuous loop, presented in Figure 1.16.

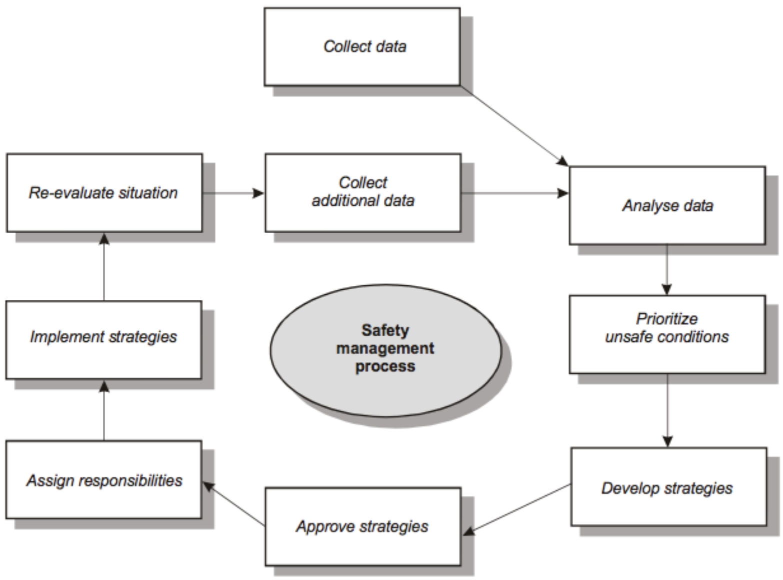


Figure 1.16: Safety management process as a continuous loop. Source: ICAO (2006b)

The first step is the acquisition of data. They should be obtained from the different parts of the system, ranging from safety reports from operation staff to recorded data from on-board data acquisition equipments. Once with the available information, safety hazards can be identified. Subsequently, developing and implementing new strategies, the loop can be closed although the process does not finish until the new situation is re-evaluated.

The safety management process requires formulating specific safety targets. Following ICAO terminology, we define:

- Safety Performance Indicator (SPI) as a measure or metric used to express the level of safety performance in a system. SPIs are generally expressed in terms of the frequency of occurrence of some causing harm as aircraft accidents per flight hours or movements.
- Safety Performance Target (SPT) or Target Level of Safety (TLS). The required level of safety performance for a system.

Figure 1.17 presents an hypothetical time series, showing the relationship between SPIs and SPTs.

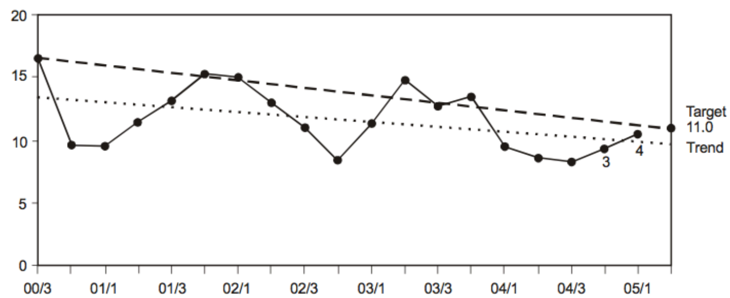


Figure 1.17: SPIs and SPTs relationship. Source: ICAO (2006b)

Safety risk probability is defined as the likelihood that an unsafe event or condition might occur. Once such probability has been assessed, the second step in the process is the assessment of the severity of the consequences of the hazard if its damaging potential materializes during operations. Safety risk severity is defined as the possible consequences of an unsafe event or condition, taking as reference the worst foreseeable situation.

As it can be seen in Figure 1.18, ICAO does not establish specific and well-defined values for safety risk probability and severity. Sometimes this has been criticized due to the probability table being only qualitative and too general and difficult to be applied within aviation business organizations.

	Meaning	Value
Frequent	Likely to occur many times (has occurred frequently)	**5**
Occasional	Likely to occur sometimes (has occurred infrequently)	**4**
Remote	Unlikely to occur, but possible (has occurred rarely)	**3**
Improbable	Very unlikely to occur (not known to have occurred)	**2**
Extremely improbable	Almost inconceivable that the event will occur	**1**

(a) Safety risk probability table

Severity of occurrence	Meaning	Value
Catastrophic	— Equipment destroyed — Multiple deaths	**A**
Hazardous	— A large reduction in safety margins, physical distress or a workload such that the operators cannot be relied upon to perform their tasks accurately or completely — Serious injury — Major equipment damage	**B**
Major	— A significant reduction in safety margins, a reduction in the ability of the operators to cope with adverse operating conditions as a result of increase in workload, or as a result of conditions impairing their efficiency — Serious incident — Injury to persons	**C**
Minor	— Nuisance — Operating limitations — Use of emergency procedures — Minor incident	**D**
Negligible	— Little consequences	**E**

(b) Safety risk severity table

Figure 1.18: Probability and severity safety risk table. Source: ICAO (2009).

A more specific approach could rely on the development of risk models for different events; e.g., Controlled Flight Into Terrain, runway excursions, etc. Although recognizing that these models have their limitations, they should be based on operating experience, using historical incident and accident rates within the aviation industry as a primary reference, but taking into account also other sources of information. In this respect, some working groups, as for example, the All Weather Operations Panel (AWOP) quantified some targets taking into account historic accident rates regarding different flight phases:

- Risk of hull loss during all phases from all causes: $1 \cdot 10^{-7}$ per flight hour or $1.5 \cdot 10^{-7}$ per mission.
- Risk of accident on approach and landing from all causes: $1 \cdot 10^{-8}$ per mission.
- Risk of collision with obstacle due to aircraft being laterally off-path or beneath the approach path: $1 \cdot 10^{-7}$ per approach.

Apart from ICAO, the european civil aviation authorities are a reference in the use of quantitative criteria in aviation safety, in relation with aircraft certification standards and operational performance criteria. "Certification Specifications and Acceptable Means of Compliance for Large Aeroplanes CS-25" represents, in the context of aircraft certification, a significant application of the use of quantitative risk criteria, see EASA (2012b). Assuming that zero risk cannot be achieved in practice, CS-25 provides a system for the quantitative classification of failures in safety systems, in terms of both the severity of the consequences and the likelihood of occurrences of the fault condition. For example, a safety criticality classification for the likelihood of occurrence used to determine performance requirements by the European Aviation Safety Agency EASA (2012b), is:

- Extremely improbable: extremely unlikely, if not inconceivable, to occur; $< 10^{-9}$ per flight hour.
- Extremely remote: Unlikely to occur when considering several systems of the same type, but nevertheless, has to be considered as being possible; 10^{-7} to 10^{-9} per flight hour.
- Remote: Unlikely to occur during the total operational life of each system, but it may occur several times when considering several systems of the same type; 10^{-5} to 10^{-7} per flight hour.
- Reasonably probable: It may occur once during the total life of a single system; 10^{-3} to 10^{-5} per flight hour.
- Frequent: It may occur once or several times during the operational life; 1 to 10^{-3} per flight hour.

As in other cases, the criteria used the historical accident record, where the risk of a serious accident due to operational and air-frame related causes was estimated as 1 per million hours of flight.

Criteria like ICAO AWOP or CS-25 should be established by government agencies to facilitate the assessment and evaluation of aviation risks for different events and areas (operations, handling, maintenance, etc.). For example, airlines could be requested to comply with a SPT in relationship to unstabilized approaches, or service providers as airport traffic management, could be required to have the "Go-Around" (G/A) numbers below an specific SPT. These criteria should be updated periodically or depending on other factors, e.g. a shorter "landing distance available" due to work in progress in the airfield, etc.

Finally, safety operational and risk management can be summarized as follows:

- In aviation, it is not possible to eliminate all risks.
- Safety risks must be managed to an ALARP level.
- Safety risk mitigation must be balanced against: time, economic costs and organizational difficulties.

Figure 1.19 represent the entirely safety risk management process as seen by ICAO (2009).

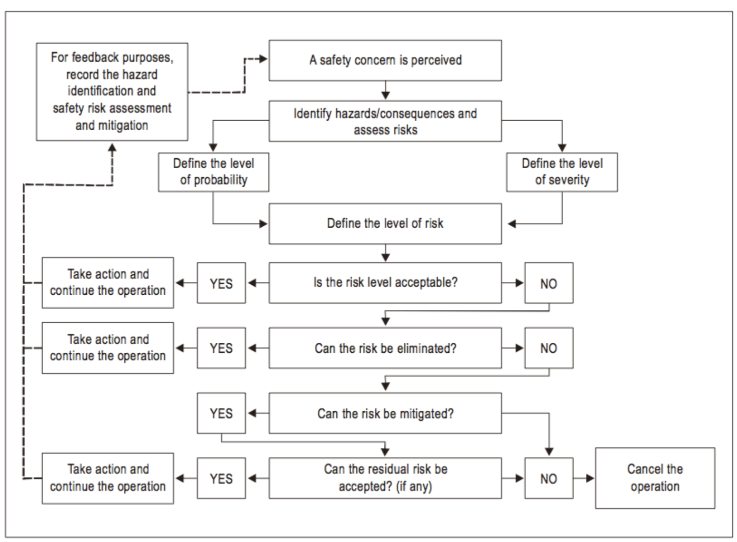


Figure 1.19: Safety risk management process. Source: ICAO (2009)

1.2.4 Risk communication

As risk management, risk communication is a relatively new field. Risk communication must provide the essential links between analysis, management staff and the rest of the organization. For this reason, it is a critical component of the whole process and it can occur at any stage of the risk assessment and management process. Different stages of the risk management process will involve various forms, levels and objectives of risk communication. For example, during the hazard identification stage, risk communication could be in the form of circulation of findings following a case study of an accident or a working group exchange of views, see Cox and Tait (1998).

Several issues should be considered when disseminating risk and safety information, see ICAO (2006b):

- Criticality of the information (e.g., urgent, “nice-to-know”, etc.)
- The target audience (e.g., crews, engineers, managers, etc.)
- Means for disseminating the information (e.g., briefings, newsletters, intranet, etc.)
- Timing strategy to maximize the impact of the message (e.g., de-icing procedures just before winter and not in summer)
- Content. Managers do not have the time to read large amounts of papers, so the key is to keep them simple and not to communicate irrelevant information. They are interested in such basic questions as: what is the problem? how could it affect the organization? how much will it cost? etc.
- Wording (e.g., consider the most appropriate vocabulary, style and tone). Written communications should meet criteria as: clarity of purpose, simplicity of language, logic and accuracy of arguments, objectives, balanced and fair consideration of facts and analysis, neutral tone and timeliness.

ICAO (2006b) suggests that disseminating risk information and safety promotion programs should be based on several different communication methods such as:

- Spoken word. It is probably the most effective method, especially if supplemented with a visual presentation. However, it is also the most expensive method, consuming time and effort to assemble the audience, aids and equipment.

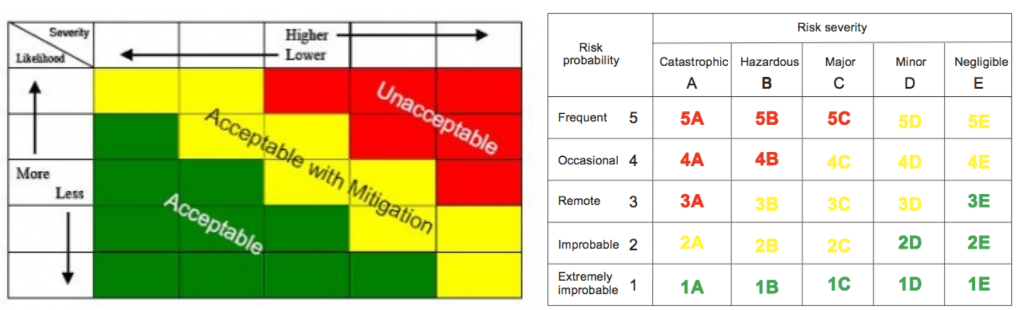
- Written word. It is, by far, the most popular method because of speed and economy. However, the proliferation of printed material tends to saturate our capacity to absorb it. Professional guidance or assistance may be desirable to ensure that the message is conveyed in an effective way.

- Videos offer the advantages of dynamic imagery and sound to reinforce particular safety messages efficiently. However, videos have two main limitations: expense of production and the need for special equipment for viewing. Nonetheless, they can be effective in getting a particular message disseminated throughout a widely dispersed organizational structure, minimizing the need for staff travel.

- Websites offer significant potential for improving in the promotion of safety and even small companies can establish and maintain a website to disseminate safety information.

- Conferences, symposia, seminars, workshops, etc. go well beyond safety promotion by helping to establish contacts with others in the safety field.

As a simple communication tool, risk matrices have been used, see Figure 1.20.



(a) (b)

Figure 1.20: Risk matrix examples

Indeed, risk matrices have been widely adopted by many organizations and risk consultants as a simple and effective approach to risk communication. However, despite having been widely accepted and used, there has been very little rigorous empirical or theoretical studies on how well risk management actually succeed in leading to improved risk management decisions. Cox (2008) argue that risk matrices experience several problematic features making it harder to asses risks, including:

- Poor resolution. Typical risk matrices can correctly and unambiguously compare only a small fraction of randomly selected pairs of hazards. They can assign identical ratings to quantitatively very different risks.

- Errors. Risk matrices can mistakenly assign higher qualitative ratings to quantitatively smaller risks. For risks with negatively correlated frequencies and severities, they can be worse than useless, leading to worse-than-random decisions.

- Suboptimal resource allocation. Effective allocation of resources to risk-reducing countermeasures cannot be based on the categories provided by risk matrices.

- Ambiguous inputs and outputs. Categorizations of severity cannot be made objectively for uncertain consequences. Inputs to risk matrices, and the resulting outputs, require subjective interpretation and different users may obtain opposite ratings of the same quantitative risks.

From an organizational perspective, an important disadvantage of risk matrices is that assessing risk through the using of a risk matrix could become the safety process in a "paper safety", and provide a false sense of safety to the organization. All these limitations suggest that risk matrices should be used with caution, to say the least.

1.3 Risk perception

Poor risk assessment can contribute significantly to poor decision-making and poor decision-making has been presented as a leading factor in fatal aviation accidents, see Jensen (1977). For this reason, a first step in safety decision-making, risk perception, must be considered a significant issues within risk framework. Risk perception could be defined as the ability to detect, perceive and asses the degree of risk associated with actual and emerging hazards, see Regan et al. (1999). Several authors have discussed this concept and have noted the difficulty of arriving at a good definition. Risk perception may be mediated by the characteristics of the context and the viewer. Contexs present a high level of risk for one person may present only low risk for another one. Underestimation of the external situation and overestimation of personal capacity leads to a misperception of the risk and this is frequently seen as a factor in aircraft accidents. Some researchers, e.g. O'Hare (1990), have developed risk judgement questionnaires to asses pilots' perceptions of the risk and hazards. Others have proposed and evaluated measures of pilots' risk-taking for selection purposes.

There are three major theories which try to explain behavior in the presence of risk, see Hunter (2002):

- Risk homeostasis, as proposed by Wilde (1994). People in any given activity have a target level of acceptable risk. People do not attempt to minimize risk, but rather, they seek to maintain an equilibrium by adjusting their behavior to maintain their target level.
- Zero risk theory, Näätänen and Summala (1974), was proposed in terms of driver behavior. According to this theory, as self-confidence increases, perceived risk diminishes to the point of zero perceived risk.
- The threat avoidance model, Fuller (1988), which suggests that people learn to anticipate hazardous events and avoid them. People rarely experience any perceived risk of an accident since those situations are avoided. This theory was also proposed in terms of driver behavior.

Risk perception and risk tolerance are related and often confounded constructs, see Hunter (2002). DeJoy (1992) noted that various risk perception formulations, based on driver research, suggest that risk-taking behavior is mediated by the level of perceived risk in the outcome, suggesting that low levels of perceived risk would be associated with riskier driving. Also, he suggests that interventions that personalize the risk to the driver should be developed, as opposed to making the risk an abstract statistical concept. Brown and Groeger (1988) provided an insightful review and discussion of the relationship between risk perception and decision-making from the viewpoint of driving research. They noted that acceptance and misperception of traffic risks present a relatively serious problem for road safety.

Another import issue, related with risk perception, is risk communication, see Section 1.2.4. As described by Fischhoff (1995), risk communication has to be taken seriously. It cannot rely on undisciplined speculation about the beliefs or motivations of people. He offers a strategy to manage risk communication,call the 7 A's:

1. All we have to do is get the numbers right.
2. All we have to do is tell them the numbers.
3. All we have to do is show them that they have accepted similar risks in the past.
4. All we have to do is show them that it is good deal for them.

5. All we have to do is treat them nice.
6. All we have to do is make them partners.
7. All of the above.

Finally, the need to understand how the aviation community form their perception of risk should be recognized as a separate field of research. Theprevious discussion seems to demonstrate that more specific aviation risk perception studies are needed to:

- Develop aviation-specific measures of risk perception and risk tolerance,
- Asses the relationship between risk perception and risk tolerance, and, even more important,
- Asses the degree with which risk perception may relate to likelihood and severity of aviation accidents.

1.4 Economic considerations about risk and operational safety management

An airline's future viability may depend on its ability to sustain the public perceived safety while flying. Risk Management and Operational Safety is therefore a major prerequisite for a profitable business and it requires a constant balancing between the need to fulfill production goals versus safety ones.

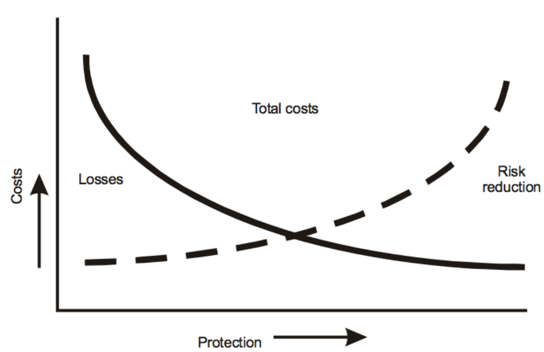


Figure 1.21: Safety versus costs. Source: ICAO (2006b)

However, safety and profit are not mutually exclusive and some quality organizations realize that expenditures on the correction of unsafe conditions may actually be an investment towards long-term profitability, as not so many organizations can survive the economic consequences of a major accident, see ICAO (2006b). For example, SAS, which at the time of the Spanair accident (August 2008) was the owner of the aircraft, estimated the accident costs in approximately 50 to 60 million dollars, taking into account the significant reduction in bookings on a year-to-year comparison. That was about 5% of the annual revenues for the company.

Because of incident and accident costs could be too expensive for an airline, comprehending the total costs of these events is fundamental to understand the economics of safety. Due to the great number of cost factors involved in incidents or accidents, performing a risk and operational safety cost-benefit analysis may be even more difficult to quantify than the costs of such events. Typical common cost factors include:

- Operational
  - Flight delays and cancellations.
  - Alternate passenger transportation, accommodation, complaints, etc.
  - Crew change and positioning.
  - Loss of revenue and reputation.
  - Aircraft recovery, repair and test flight.
  - Catering.
  - Training.
  - Others.
- Technical
  - Aircraft on ground.
  - Aircraft recovery and repair.
  - Test flight.
  - Technical documentation and incident investigation.
  - Repair team accommodation.
  - Recertification.
  - Others.

The costs of these occurrences can be classified into two basic types: direct and indirect, see ICAO (2006b):

- Direct costs. These are the obvious costs which are fairly easy to determine. They mostly relate to physical damage and include rectifying, replacing or compensating for injuries, aircraft equipment and property damage. The high costs of an accident may be reduced by insurance coverage. Some large organizations effectively self-insure by putting funds aside to cover their risks.

- Indirect costs. While insurance may cover specified accident costs, there are many uninsured costs. An understanding of these uninsured, or indirect costs, is fundamental to understand the economics of safety. Indirect costs include all those items that are not directly covered by insurance and usually total much more than the direct costs resulting from an accident. Such costs are sometimes not obvious and are often delayed. Some examples of uninsured costs that may accrue from an accident include:

  - Loss of business and damage to the reputation of the organization. Many organizations will not allow their personnel to fly with an operator with a questionable safety record.
  - Loss of use of equipment. This equates to lost revenue. Replacement equipment may have to be purchased or leased. Companies operating a one-of-a-kind aircraft may find that their spares inventory and the people specially trained for such an aircraft become a surplus.
  - Loss of staff productivity. If people are injured in an accident and are unable to work, many States require that they continue to be paid. Also, these people will need to be replaced at least over the short term, incurring the costs of wages, overtime (and possibly training), as well as imposing an increased workload on experienced workers.
  - Investigation and clean-up. These are often uninsured costs. Operators may incur costs from the investigation, including the costs of their staff involvement in the investigation, as well as the costs of tests and analyses, wreckage recovery, and restoring the accident site.
  - Insurance deductibles. The policyholder's obligation to cover the first portion of the cost of any accident must be paid. A claim will also put a company into a higher risk category for insurance purposes and, therefore, may result in increased premiums. Conversely, the implementation of a comprehensive SMS could help a company to negotiate a lower premium.
  - Legal action and damage claims. Legal costs can accrue rapidly. While it is possible to insure for public liability and damages, it is virtually impossible to cover the cost of time lost handling legal action and damage claims.

  - Fines and citations. Government authorities may impose fines and citations, including possibly shutting down unsafe operations.

1.5 Safety prevention and incentives for aviation safety

The benefits of safety are undeniable, not only from a moral standpoint, but also from an economic point of view. As established by Vasigh et al. (2008), some of the potential economic benefits of aviation safety include:

- Strengthened consumer demand.
- Strengthened labor supply.
- Reduced insurance costs.
- Lower cost of capital.
- Lower liability risk.
- Reduced costs associated with government fines or penalties.

Today's competitive environment is forcing airlines to reduce operating costs. For this reason, some people will assert that some airlines occasionally may cut corners that compromise safety in the interests of greater profit. Vasigh et al. (2008) argue that just the opposite is probably true because there are strong incentives for airlines to avoid incidents or accidents. They emphasize the following broad categories:

- Asymmetrical media coverage. Media does not document the thousands of routine safe flights a day and the low probability of aviation accidents. However, any minor safety incident suffered by an airline will draw a sensationalist and extensive media coverage, showing their logo to millions of consumers across the world.

- Passengers' reaction. An airline that is perceived to be less safe, as a result of an incident or accident, is likely to see a decrease in demand compared to "safer" airlines. In addition, an aviation accident may have a long-term impact on an airline's demand because perceptions are difficult to change and may persist for an extended period of time, see Squalli and Saad (2006). Although this economic reasoning seems to be logical, empirical studies have had, however, difficulties in proving a decrease in demand and some extensive studies of accidents in the United States found that there was no statistically significant decrease in demand.

- Labor reaction. As a result of the perception of reduced safety, employees, particularly flying crew, could leave the company or push the union to enforce new safety measures. Moreover, an accident, or a series of serious incidents, could make it more difficult for an airline to attract high-quality employees. Apart from that, employees may demand better compensation for having to work in an uncertain and less safe environment.

- Financial concerns. An accident causes great uncertainty over the future of the airline in question. For this reason, the stock market may react negatively, particularly with one that involves fatalities. Some studies found that, on average, aviation accidents caused a 0.94% equity loss for the firm on the first day of trading. Moreover, if the accident was proved to be the airline's fault, then the equity value dropped by 2.2% in long term.

- Insurance costs and liability risk. Insurance companies will pay out various liability and damage claims for the airlines when an aviation accident occurs, so that airlines suffer little direct financial loss from an accident. However, as a result of this, the airline's insurance premiums are likely to increase considerably in the future, particularly if the airline is determined to be liable. A hike in insurance rates will occur for several years, and this could have a significant effect on the airline's profit margins.

- Government enforcement. Aviation regulations are designed to prevent airlines from violating safety procedures, becoming the threat of government penalties in a real market incentives. In a severe violation in safety practices, aviation authorities can order an airline to cease operations cutting off the airline's revenue.

1.6 The effectiveness of safety management systems in the commercial aviation

In accordance with ICAO (2009), aviation organizations have incorporated SMS as a way of managing safety risk. However, the empirical evidence reviewed to date has not yet provided a significant demonstrable safety improvement that can be directly attributable to SMS, see Thomas (2012). According to this author, this could be due to:

- Although ICAO (2009) adopts a systematic approach to the management of safety, ICAO SMS is defined in a simplistic way with little detail and a poor scientific framework. For example, according to ICAO (2006b), safety industrial research in 1969 indicated what is known as the 1:600 rule for every 600 reported occurrences with no injury or damage (incidents), see Figure 1.4. However, Hall et al. (2008) established an interesting conclusion. They used U.S. accidents and incidents as a sample and they observed that the number of reported incidents was close to the number of accidents; when one would expect to see a much higher number of incidents compared to accidents. To them one possible explanation for this phenomenon would be that some incidents were unreported. They carried out an analysis in which unreported incidents were estimated to be 28.8%.

- Modern SMS could be defined as an arbitrary collection of activities that were deemed necessary actions to discharge responsibilities under the new age of delegated responsibility of self-regulation. Moreover, SMS represent just an accumulation of a wide range of "common-sense interventions".

- In commercial aviation domain, the lack of clear relationships between the performance of components of an SMS and objective data is likely to be influenced by the inherent lack of frequency of high consequence failures.

Although evaluating the effectiveness of SMS in managing commercial aviation safety is extremely difficult, a new approach supported by scientific framework would be more appropriate to increase the effectiveness of SMS.

1.7 A framework for risk analysis and safety decision-making

We describe now a schematic framework that formalizes standard risk analysis, assessment, and management methods as in Haimes (2009) or Bedford and Cooke (2007), adapted to the classic proposal of Garrick and Kaplan (1981). We shall use such framework within the three case studies which form the core of this Thesis. The framework uses influence diagrams to structure problems. For simplicity, we shall assume that losses can be monetized as costs. The participating agents is assumed to be a expected utility maximizer, see French and Ríos Insua (2000).

Figure 1.22 shows an influence diagram, see Pearl (2005), that displays the simplest version of a risk management problem.

An influence diagram is a directed acyclic graph with three kinds of nodes:

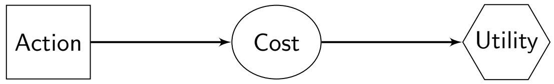


Figure 1.22: Basic influence diagram.

decision nodes, shown as rectangles; uncertainty nodes, shown as ovals; and value nodes, shown as hexagons. Arrows into a value or uncertainty node indicate functional and probabilistic dependence, respectively. Thus, the utility function at the value node depends on its immediately preceding nodes and probabilities at a chance node are conditional on the values of its direct predecessors. Arrows into a decision node indicate that when the decision is made, the values of its preceding nodes are known. In Figure 1.22, the rectangle represents the set $\mathcal{A}$ of possible decisions, the oval represents the costs associated with the decisions, and the hexagon represents the net consequences in terms of the decision maker's utility function. It corresponds to a problem in which an organization has to make a decision a from a set $\mathcal{A}$ of choices. The cost c that results from each decision is uncertain and is modeled through the density $\pi(c|a)$. This cost may reflect the fact that the outcome for a particular decision is uncertain, or that the cost associated with a particular outcome is uncertain, or both. The utility $u(c)$ of the cost is a decreasing and typically. One seeks the decision that maximizes the expected utility

$$\psi = \max_{a \in \mathcal{A}} \left[\psi(a) = \int u(c)\pi(c|a)dc \right].$$

In practice, the cost for a particular action is complex and conditional on the outcome; it often includes fixed and random summands. The organization will typically perform a risk assessment to:

1. Identify disruptive events $E_1, E_2, ..., E_k$ (these may be assumed to be mutually exclusive);
2. Assess their probabilities of occurrence, $P(E_i|a) = q_i(a)$, and;
3. Assess the cost c_i, conditional on the occurrence of E_i and decision a (these costs are typically random).

It is convenient to let E_0 be the event such that there are no disruptions, with probability $q_0(a)$. Figure 1.23 shows the influence diagram that extends the previous formulation to include risk assessment.

Let (a) be the vector of probabilities corresponding to decision a, and let $\pi_i(c|a)$ be the cost density for decision a, if event E_i occurs. Then, the density of

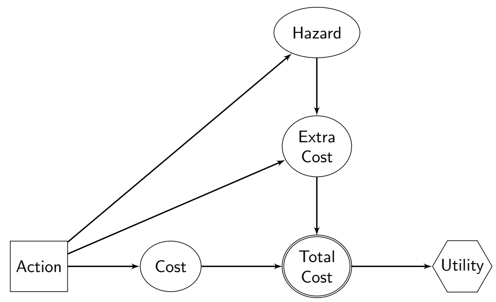


Figure 1.23: Influence diagram with risk assessment.

the cost for decision a is the mixture

$$\sum_{i=0}^{k} q_i(a)\ \pi_i(c|a),$$

Once the risk assessment is performed, the organization aims at maximizing the expected utility decision, by solving:

$$\psi_r = \max_a \left[\psi_r(a) = \sum_{i=0}^{k}\ q_i(a) \int u(c)\pi_i(c|a)\,dc \right].$$

In some cases, the probabilities $q_i(a)$ are themselves uncertain, e.g., if one is combining assessments from multiple experts. In that case, one can describe that uncertainty through a distribution $g(a)$ on the unit simplex $S \subset \mathbb{R}^{k+1}$ and solve:

$$\psi_r = \max_a \left[\psi_r(a) = \int_S g(a) \left(\sum_{i=0}^{k}\ q_i(a) \int u(c)\pi_i(c|a)\,dc \right)\ d(a) \right].$$

Note that this maximizes the utility with respect to uncertainty from two different sources

- The randomness in the costs;
- The imprecise knowledge about the disruption probabilities.

Consider now the difference $\psi - \psi_r$. This is non-negative, as ψ describes a decision problem without including the costs associated with disruptive events, whereas ψ_r relies upon risk assessment and is more realistic. To reduce this difference, organizations often undertake a risk management strategy. Risk management introduces an additional set of choices $\mathcal{M}$, e.g., contingency plans or insurance policies which tend to lower the costs associated with particular disruptions, lower the chance of disruption, or both.

As an example of risk management, imagine that an airline company is studying to open up a new route just for the summer time. The company considers two possibilities, these being the decisions in $\mathcal{A}$: to operate with the own support of the company (aircraft, flight and cabin crew, etc.) or to operate as a wet lease agreement (a leasing arrangement in which aircraft, complete crew, maintenance, and insurance is provided to the airline). The risk assessment indicates the possibility of a company strike and/or the non-availability of wet lease in such season. The company, therefore, considers to sign a temporary agreement with Unions (which would protect against the costs associated with strike), or trying to operate the wet lease (at more expense, but with less chance of striking), or doing neither. These choices are the elements in $\mathcal{M}$.

In principle, one could take the cross product of sets $\mathcal{A}$ and $\mathcal{M}$, and then, solve for ψ_r over this extended set. But in practice, it is often helpful for managers to keep these distinct. The risk management solution remains the same,

$$\psi_m = \max_{(a,m)\in\mathcal{A}\times\mathcal{M}} \psi_r(a,m), \tag{1.1}$$

where, in an obvious extension of previous notation,

$$\psi_r(a,m) = \sum_i q_i(a,m) \int u(c)\pi_i(c|a,m)\,dc.$$

As before, a slightly more complicated formula applies when there is uncertainty in the $q_i(a,m)$ probabilities. Figure 1.24 shows the influence diagram for a risk management problem.

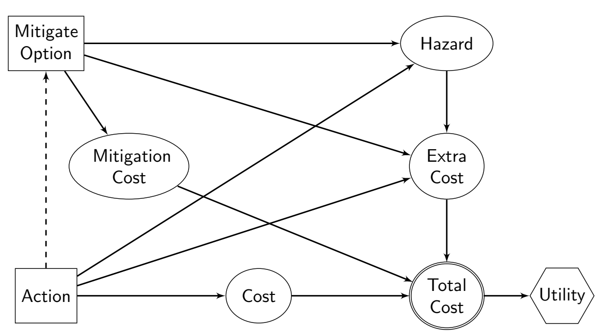


Figure 1.24: Influence diagram with risk management.

Since risk management extends the set of choices, then $\psi_m \geq \psi_r$, but both are still smaller than ψ. The problem described in 1.1 can be viewed as an example of a sequential decision problem and could be represented as a decision tree: first, one picks the design, and then one picks a choice in $\mathcal{M}$, with the corresponding uncertain nodes. In general, problems of this kind require dynamic programming, since the decision at each time period depends on the likely future outcomes, deeper in the tree. But trees can be a problematic representation, since the choice sets need not be discrete but could be continuous. Clearly, additional complexity arises if there are many levels of sequential investment, if one allocates risk management resources according to a portfolio analysis, and/or if there are multiattribute utility functions.

Finally, we need a procedure to communicate risks and risk management strategies. As we mentioned, risk matrices have been widely adopted by aviation organizations as a simple way to risk communication. However, due to several reasons, see Section 1.2.4, we shall not follow this approach. Instead, we shall propose for each specific case study what we consider more effective graphs, see for instance Figure 1.25.

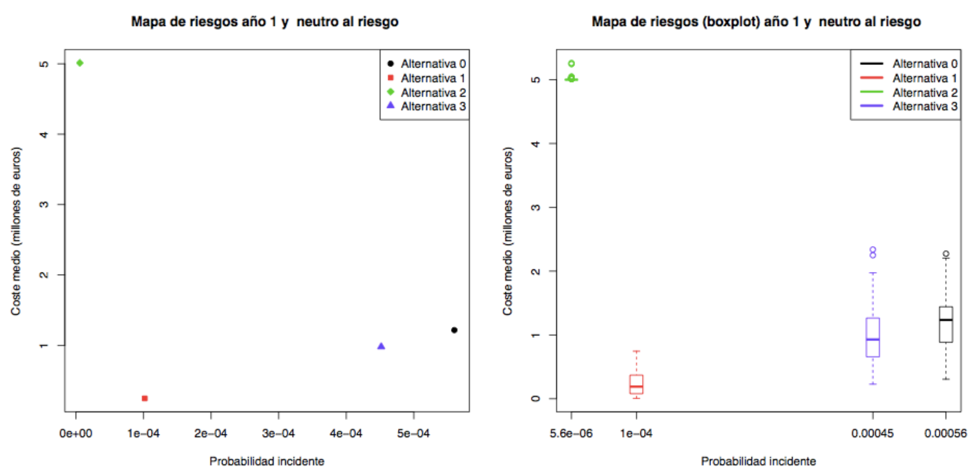


Figure 1.25: Risk map example.

This Figure is an example of a risk map. In this particular case, average cost versus probability of the incident is represented. As we can observe, four different alternatives are represented in four colors. The left graphic is a scatter plot and the right one a boxplot risk map. We propose this specific graphical presentation of the problem to get over some of the problematic features inherent to risk matrices.

1.8 The flight ahead

In the rest of the PhD Thesis we shall apply the above framework to three relevant case studies in commercial aviation risk management. Each example will be increasingly complex. In the first case study, we will provide a risk analysis procedure undertaken to mitigate problems in relation with the unintentional deployment of escape slides when the aircraft is reaching the parking position. This kind of events is relatively common for airlines under normal operations, becoming a non-negligible safety risk with relevant economic implications. In the second one, we will purpose a fueling for holding decision-making problem at arrival. Due to jet fuel price rises, the running-low-on-fuel events may became a significant safety problem, specially for some airlines, in which fuel costs are the most limiting share in their budgets. The last case study deals with a major aviation safety threat, the runway excursion at landing. We will purpose a probabilistic runway overrun model to help the airline community and aerodrome operators in assessing and managing this threat. We will use these three case studies to purpose a Bayesian approach to manage risk, and take safety decisions, within the commercial aviation domain.

Chapter 2

Unintentional Slide Deployment under Normal Operation

2.1 Introduction

As we mentioned in Chapter 1, increasing competition within a shrinking economy is forcing airlines to reduce costs. This might eventually affect safety, in spite of being a critical factor in the aviation industry. Within such complicated context, it is worth noting that risk analysis in this industry has been based on relatively simple methods to identify, assess and communicate risks, see ICAO (2006b)and ICAO (2009). As an example, expected loss values are frequently used to summarize risks, even though this may not be adequate to capture low probability high consequence events usually associated with safety-critical systems, as it happens in air transportation, see Haimes (2009). Also, standard aviation safety procedures tend to promote risk matrices in spite of well-known criticisms, see Cox (2008). For this reason, there is a need to develop and improve current procedures and tools to analyze risk factors in an increasingly complex commercial air transportation system as we aim to do in this Thesis. Jayakody and Place (2009) support such view.

In this chapter, we shall analyze a relatively important air transportation incident: the unintended deployment of slides under normal operations within an airline. Due to the current commercial aircraft dimensions, manufacturers have been required to develop and install inflatable slides at emergency and exit doors according to certified standards, see Figure 2.1.

These slides facilitate escaping from the aircraft to the ground level during emergencies. For example, the Federal Aviation Administration (FAA) and the European Aviation Safety Agency EASA (2012b) require slides on all aircraft exit

Figure 2.1: Inflated evacuation slide on a B747.

doors which are 1.8 meters (6 ft) or more above ground level, as the evacuation of the entire aircraft is required to be done in 90 seconds using 50% percent of the available evacuation exits. Standard Operating Procedures (SOP) establish that cabin crew members must set exit doors in armed (or automatic) mode prior to taxi out for departing. In the event of an emergency, when the door is opened, the slide deploys automatically providing a means of getting out of the aircraft quickly.

Many slides are unintentionally deployed under normal operations every year all around the world, becoming a safety issue for passengers and handling staff, see Figure 2.2, also with relevant financial implications.

Figure 2.2: Slide deployment event on ground.

A IATA (2005) report outlines this problem from an economical point of view, estimating a cost of around USD 20 million per year across the airline industry. Because there are so many variables involved in this type of incidents, as defined in ICAO (2010), actual costs may be difficult to calculate. However, for major airlines, the key costs mainly refer to repairing the slide system as well as to potential delays originated by the incident.

We provide a formal risk analysis for this problem, see Bedford and Cooke (2007) or Bier and Cox Jr (2007) for methodological introductions. Unlike standard practice in the aviation field, our analysis is based on historical recorded data as much as possible, relying on expert opinion to fill the gaps whenever data is not available. For that purpose, we draw on rigorous elicitation methods, as described in French and Ríos Insua (2000).

We first assess the entailed risks providing a model for the occurrence of such incidents and its associated costs, and combine them to provide forecasts for the corresponding total costs. As these are deemed too high, we then consider possible countermeasures and evaluate which is the most effective. We conclude with some discussion.

2.2 Risk assessment

We start by assessing risks in relation with unintended slide deployment under normal operations in a main commercial airline, within the classic risk analysis framework. An exploratory analysis of monthly incident rates shows an increasing trend, suggesting the growing relevance of this problem, see Figure 2.3.

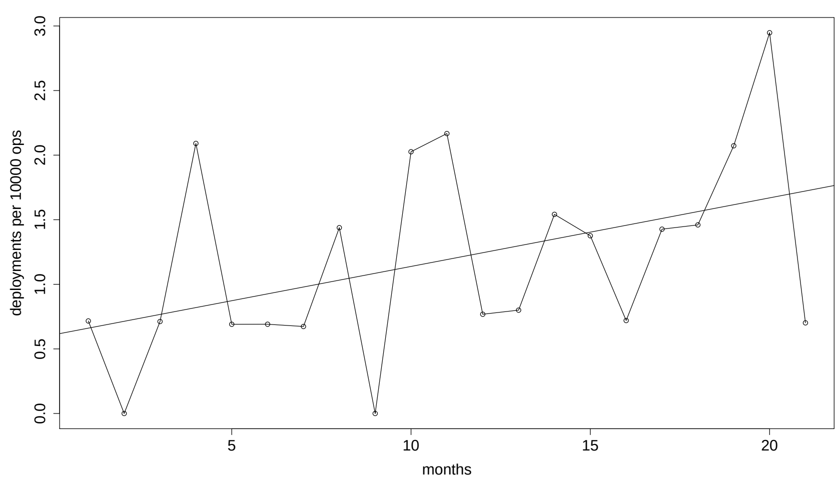


Figure 2.3: Slide deployment time series

2.2.1 Incident data analysis

We start by making inferences about the occurrence rate of this type of incidents, as well as forecasts of the number of incidents. A maximum likelihood estimate for the incident proportion for a given company over a twenty one month period is 0.00011, for 35 incidents over 304,514 operations, or approximately, 1.1 incidents per 10,000 operations.

Through discussion with experts and a literature review, we identified four factors potentially affecting unintended slide deployment under normal operations: aircraft type, airport, pairing day and flight turn. Under noninformative priors, we have performed equal proportion tests in relation with those factors, based on a beta-binomial model (for two proportions) or a Dirichlet-multinomial model (for several proportions), see French and Ríos Insua (2000) for details. Table 2.1 summarizes the results obtained.

Table 2.1: Test results concerning factors potentially affecting incidents.

Factor	Relevance	Factor levels
Aircraft type	Yes (Moderate)	A $>$ B
Airport	No	Nearly 50
Pairing day	Yes (Moderate)	First $>$ Second $>$ Third
Flight turn	Yes (Moderate)	First $>$ (Second, Third)

As an example, as far as the aircraft type is concerned, the data available are 30,355 operations, with 7 incidents, for type A aircrafts, and 262,825 operations, with 28 incidents, for type B aircrafts. A 90% credible interval for the difference of incident proportions between type A and B airplanes is [0.000011, 0.0003], which suggests a slightly bigger incident proportion for type A planes.

Thus, we believe that the following factors might have influence over the proportion of incidents:

- Aircraft type. There seems to be a slightly bigger proportion of incidents for the A fleet, for which most flights are long haul, than for the B fleet, with most flights being short haul. This might be due to a slightly poorer situational awareness at long haul flights.

- Pairing day. Considering a typical three days on-duty pairing, it seems that there are more incidents on the first day than on the second one than, in turn, on the third day of a pairing. This might be due to poor situational awareness, after a day off, which gradually increases flight after flight, specially on long haul flights.

- Flight turns. We have considered the usual three flights per day on short haul flights, and one flight per day, on long haul ones. In this context, there seems to be a bigger proportion of incidents in the first turn. For the second and third turns in short haul flights, the proportions seem similar. On long haul flights, poor situational awareness could provide an explanation. On short haul flights, time pressure to be on schedule, plus connecting passengers putting pressure on cockpit and cabin crew members to leave the aircraft as soon as possible to reach connecting flights, could be a contributing factor to the incident.

As a consequence, we have fitted a binomial logistic regression model to the incident proportions, with

$$\begin{aligned}(x_i, n_i, y_i), i &= 1, ..., k \\ y_i|\theta_i &\sim Bin(n_i, \theta_i) \\ logit(\theta_i) &= \alpha + \beta x_i\end{aligned} \tag{2.1}$$

where i designates the factor levels we have considered relevant; x_i, the factor level values; n_i, the number of operations under such conditions; y_i, the number of incidents for factor level i; θ_i, the proportion of incidents under level i and, finally, α and β, the parameters to be estimated. We have identified $k = 9$ relevant levels, described in Table 2.2, which provides the data used to fit the model.

Table 2.2: Data concerning factors potentially affecting incidents.

Case	Operations	Incidents	Factor levels	Coding
i	n_i	y_i	(fleet,day,turn)	x_i
1	29,702	3	B,Fst,1	1,1,1
2	59,661	7	B,Fst,Oth	1,1,2
3	44,159	6	B,Snd,1	1,2,1
4	46,257	6	B,Snd,Oth	1,2,2
5	28,910	2	B,Thrd,1	1,3,1
6	55,193	4	B,Thrd,Oth	1,3,2
7	15,245	6	A,Fst,1	2,1,1
8	1,516	0	A,Fst,Oth	2,1,2
9	13,713	1	A,Thrd,1	2,3,1

Note that the fleet factor has two values, therefore, we estimate one β parameter for it. The pairing day has three factor levels, thus we need to estimate two β parameters for it. Finally, the flight turn has two values, therefore requiring one β parameter. We have used vague normal priors, adopting the strategy in Gelman et al. (2009) and Gelman and Hill (2007). The posterior means for the parameters were -9.03 for

α and (0.83, 0.06, -0.77, -0.03) for the β parameters, with corresponding standard deviations (0.39, 0.52, 0.41, 0.46, 0.38). Only α and the first β parameters seemed a posteriori significant. They were the only ones retained in the final model.

With a view towards risk management, we have tested in which operational flight phase, and who could be made responsible for deployments, based on Dirichlet-multinomial models, see Ríos Insua et al. (2012). Table 2.3 summarizes the results.

Table 2.3: Operational phase and staff potentially affecting incidents.

Factor	Relevance ranking
Operational phase	Arrival $>$ Departure $\gg$ Refueling (Turnround)$>$ Preflight (Stopover)
Staff involved	(a, b) $>$ (c, d, e, f , g, h, i)

This suggests that:

- Most incidents take place at arrival, possibly because these are the phases in which more stress accumulates, due to increasing scheduled time pressure.
- Most incidents seem to be caused by (a, b) personnel, as this tends to operate closer to the slides.

We have also analyzed the reported causes of incidents, based on the "Human Factor Analysis and Classification System" framework FAA document, see Shappel and Wiegmann (2000). Within it, unsafe acts of crew are classified into Errors (decision, skill-based and perceptual errors) and Violations (routine and exceptional). All causes of incidents reported within our database can be described as skill-based errors: 7 inadvertent use of handles (door or arm/disarm), 9 failures in prioritizing attention (interruptions) and 19 omitted steps in procedure (non compliances). A posteriori, we model the proportions of error types as a Dirichlet distribution with parameters 8, 10 and 20.

2.2.2 Modeling incident costs

Unintentional slide deployment during normal operations could potentially cause serious, even fatal, injuries to crew and ground staff working in the vicinity of the aircraft. However, we have concentrated here on economic impacts, mainly due to lack of reported data concerning injuries over the period of interest, and even over the whole history of the incumbent airline. Because of the difficulties in getting access to indirect operational cost data, such as ground expenses or passenger services, the following factors affecting direct costs have been taken into account:

- Cost of repairing the slide, which comprises:
  - Maintenance crew labor costs to remove the deployed slide and install a suitable one, when applicable, which essentially depends on the time T_m for required maintenance.
  - Transportation costs for the slide, C_t.
  - Maintenance work costs, C_m. This will depend on the type of aircraft and emergency exit affected. Costs may depend also on whether the company repairs the slide in-house, or needs to repair it at external workshops.
- Ground delay associated costs, described as the induced delay T_d times the cost C_d per unit time associated with the delay.

As a consequence, the incurred costs C per incident are modeled through the random variable

$$C = Lab \times T_m + C_t + C_m + C_d \times T_d, \tag{2.2}$$

where Lab represents the labor maintenance costs per hour.

We describe now the component costs used in our analysis, which is done in euros (EUR):

- The maintenance labor cost Lab is 65 EUR/hour per technician. As regards T_m, we use judgmental elicitation as follows. An expert provided assessments for the minimum (30 minutes), the maximum (60 minutes) and the most likely (45 minutes) work durations. Then, we applied the methodology in Galway (2007). To mitigate expert overconfidence, we assume a triangular distribution with .05 and .95 quantiles in the minimum and the maximum, leading to a triangular distribution $\mathcal{T}(0.385, 0.75, 1.115)$, measured in hours.
- For C_t, we use judgmental elicitation as before. We asked an expert to provide assessments for the minimum (60 euros), the maximum (180 euros) and the most likely (110 euros) transportation costs. We assess it as a triangular distribution $\mathcal{T}(34, 110, 210)$.
- C_m is described as the mixture

$$C_m = q \times C_m^i + (1 - q) \times C_m^e,$$

where q represents the proportion of slides repaired in-house and superscripts i and e refer to in-house and external maintenance workshop, respectively.

- For q, we used judgmental elicitation with an expert. He assessed that around 80% of the slides are repaired externally, expressing little uncertainty about such assessment. As a consequence, we fit a beta distribution $\mathcal{B}(16, 4)$, after checking for consistency.
- The costs C_m^i and C_m^e will depend on the type of slide repaired, expressed as in Table 2.4, for various types of doors in aircraft A and B.

Table 2.4: In-house and external cots for slides depending on door and airplane affected.

	A1	A2	A3	A6	A6w	Bf	Ba	Bw	B2/3
C_m^i	4160	4040	2400	3630	3210	1840	1840	1630	1430
C_m^e	6429	4850	5785	7423	4946	2605	2323	4571	4741

We have observed the following incidents for each type of emergency and exit door, which leads us to the following Dirichlet posterior parameters under a vague prior, with separate models for A and B aircraft types, see Table 2.5.

Table 2.5: Incidents and posterior parameters for A and B aircraft type doors.

	A1	A2	A3	A6	A6w	Bf	Ba	Bw	B2/3
Incidents	4	2	1	0	0	17	4	1	5
Parameters	5	3	2	1	1	18	5	2	6

Note that A1 and Bf gates, which are the most affected by this type of incidents, are attended by type a/b personnel, highlighted above.

- We deal now with delays T_d for the recorded incidents. Out of 35 events, 13 incidents entailed no delay, or the delay was absorbed by the route network. Within the remaining 22 times, we observed 20 ”standard” non-zero delays and two extremely long delays (15 and 20 hours, approximately) associated with A type aircrafts departing from a certain airport. We provide the histogram of the non zero and non extreme data in Figure 2.4.

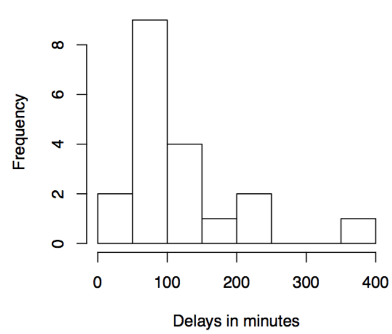


Figure 2.4: Nonzero and non-extreme delays in minutes for incidents.

We, therefore, decompose the delay T_d through the mixture

$$T_d = p_0 \; I_0 + p_1 \; F_d$$
$$p_0 + p_1 = 1$$
$$p_0, p_1 \geq 0.$$

The first component describes the zero delays, where I_0 denotes the indicator function at 0. The second one, the positive delays. Through a standard noninformative beta-binomial model we get

$$p_0 | data \sim Be(14, 23).$$

We model non-zero delays, extreme and non-extreme ones, considering separately the delays for type B aircrafts (F_{d_B}) and type A aircrafts (F_{d_A}). Indeed, we represent

$$F_{d_B} \sim Wei(\theta = 0, \alpha, \beta),$$
$$F_{d_A} \sim p \; Wei(\theta = 0, \alpha, \beta) + (1 - p) \; Wei(\theta, \alpha, \beta),$$

where we consider the following parametrization for the Weibull density

$$f(x \mid \theta, \alpha, \beta) = \alpha \frac{(x - \theta)^{\alpha - 1}}{\beta^{\alpha}} \exp(-((x - \theta)/\beta)^{\alpha}),$$

where θ, α and β are, respectively, the location, scale and shape parameters.

We use a reference prior for the Weibull parameters, as in Sun and Berger (1995). For p, we have considered a beta prior with mean around 0.75 and standard deviation 0.22, whereas for the location parameter θ in the Weibull component of the mixture for extreme data, we have used a uniform distribution between 11 and 16 hours. We have used a Metropolis within Gibbs sampling scheme to simulate from the posteriors with adequate model fit, as shown in Figure 2.5.

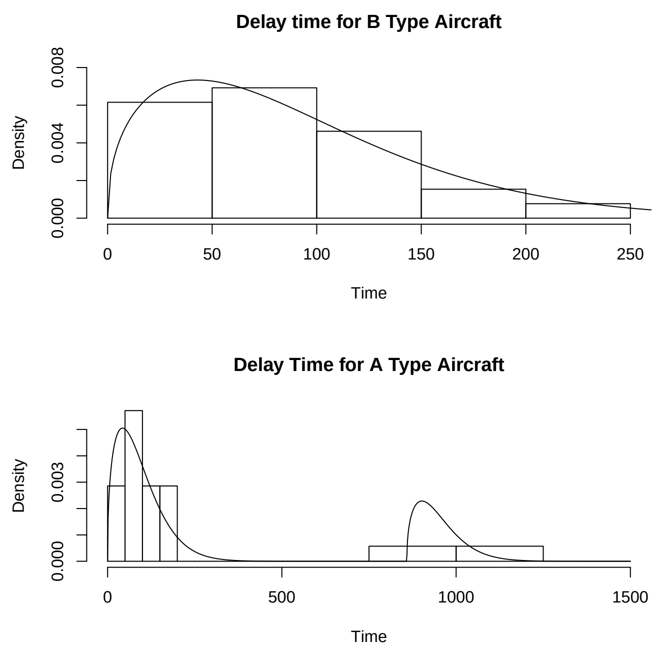


Figure 2.5: Histograms of delay times in minutes for aircrafts A and B and adjusted model using the posterior mean (continuous line).

- As for the delay costs C_d, we use a model based on a study by Cook and Tanner (2009). We have considered three main cost components: costs related with passenger delay, marginal crew costs and marginal maintenance costs. As established by Cook and Tanner (2009), total costs are often dominated by the passenger component which is split into "hard" (related with rebooking, compensation care, etc.) and "soft" costs (in relation with perceiving the airline as unpunctual and choosing, consequently, another one). Marginal crew costs refer to the cost of crewing for additional minutes over and above those planned, whereas marginal maintenance costs entail factors such as the mechanical attrition of an aircraft waiting at gates. We have adopted figures for long and short haul scenarios based on Cook et al. (2009) and Cook and Tanner (2009) data and models, with minimum, most likely and maximum values in both scenarios. After updating figures for inflation, we have the following costs in EUR per minute, see Table 2.6.

Table 2.6: Incurred Costs C_d for A and B (euros/min).

	A Flights (Min, most likely, max)	B Flights (Min, most likely, max)
Passenger Hard Costs	(0.12, 0.19, 0.24)	(0.12, 0.19, 0.24)
Passenger Soft Costs	(0.06, 0.19, 0.22)	(0.06, 0.19, 0.22)
Marginal Crew Costs	(0.00, 14.00, 39.00)	(0.00, 7.90, 16.59)
Marginal Maintenance Costs	(0.65, 0.81, 0.97)	(0.38, 0.47, 0.56)
Total Costs	(0.83, 15.19, 40.27)	(0.56, 8.75, 17.61)

We then drew 10,000 observations from the distribution (2.2) of incurred costs C, by sampling from its constituents, which leads us to the predictive cost distribution per incident shown in Figure 2.6, which depends on the flight type.

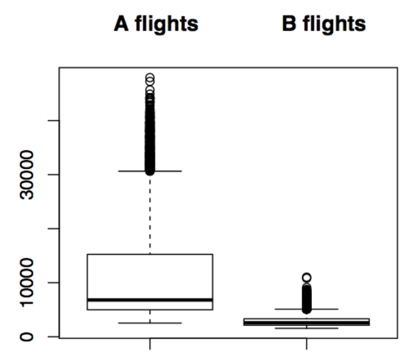


Figure 2.6: Predictive costs per incident for A and B aircraft types.

Figure 2.7 also provides the contribution of various component costs, which are dominated by delay related ones and, then, maintenance work costs.

In Table 2.7, we provide the mean and median for the predictive costs for both aircraft types, together with the 0.95 and 0.98 quantiles, which may be relevant in our context.

Table 2.7: Costs associated with an incident for A and B aircraft type.

	Type A	Type B
Mean	10970	2959
Median	6808	2590
$Q_{0.95}$	30481	5503
$Q_{0.98}$	35189	6129

As we may see, the costs per incident can be quite considerable, specially for type A flights. We now assess the annual costs associated with the incident.

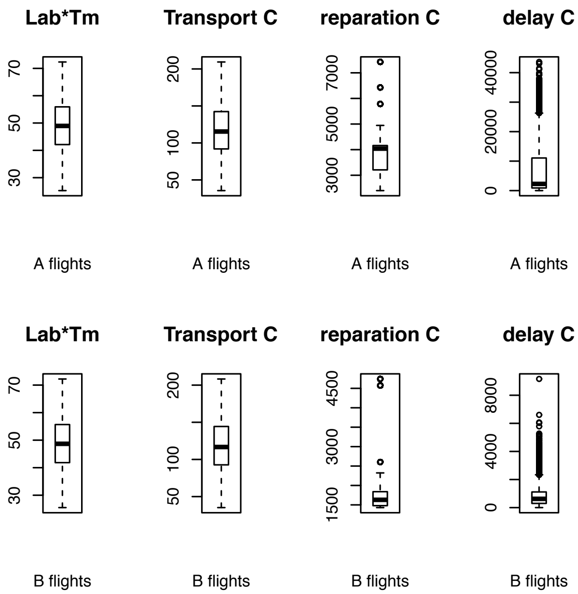


Figure 2.7: Cost components for type A and B flights.

2.2.3 Risks associated with slide deployment

We combine, through simulation, our likelihood and consequence models to complete the risk assessment. In a current typical year, the incumbent airline flights around 175,000 operations, out of which 17,000 are of type A and 158,000 are of type B.

Based on 1,000 replications of one year operations, reflected in Figure 2.8, the average annual cost due to incidents is EUR 663,400, whereas the median cost is EUR 655,200.

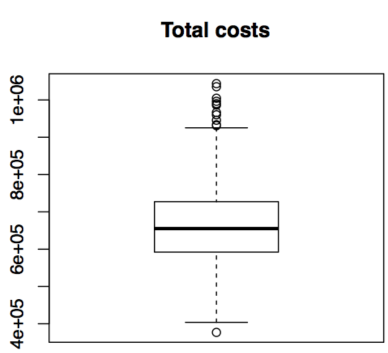


Figure 2.8: Annual costs due to incident for a commercial airline.

The 0.95 and 0.98 quantiles are, respectively, EUR 836,863 and EUR 893,314. In the current economical setting, this is a non-negligible cost which needs to be managed.

Figure 2.9 provides the annual cost components due to the incident for the nine flight levels, see Table 2.2. Note that A flights are the major contributors to the airline costs in relation with this incident.

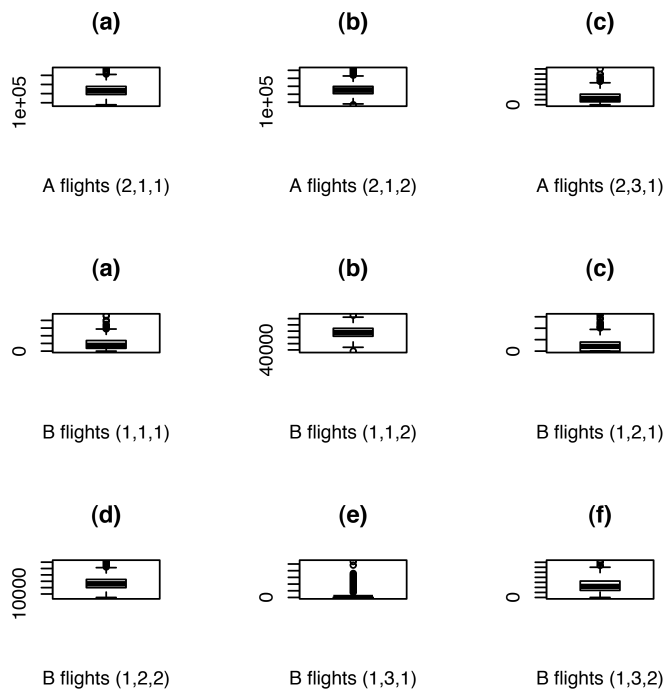


Figure 2.9: Annual costs for various types of flights.

2.3 Risk management

So far, we have identified and analyzed the effects of unintentional slide deployment. We shall describe now several relevant countermeasures aimed at mitigating this hazard to an acceptable level. Thus, we face now how to manage the risks associated with the incident incumbent.

2.3.1 Available countermeasures

Based on our logistic regression model (2.1), the tests performed in Section 2.2.1, a literature review and brainstorming sessions with airline experts, we devised the following possible countermeasures.

Countermeasure 1: Procedure revision

One possibility is the revision of current procedures in order to avoid interruptions, based on comparisons with procedures and rules of other companies at the same business level. As an example, at departure, the incumbent company procedure establishes that flight attendants must arm slides prior to push-back when the aircraft is still with parking brakes set, once doors are closed and the jet-way is moved away from aircraft. Other companies arm slides just prior to taxi, after engine startup. Similarly, upon arrival, the incumbent company procedure establishes disarming slides after engine shutdown in parking position. Other companies disarm slides just before reaching the parking position, while the aircraft is still taxing in.

This countermeasure, which tries to separate on time opening/closing and slide arming/disarming procedures, would practically eliminate all incidents due to errors and interrupted procedures, whereas it would have virtually no effect upon other incident causes. This countermeasure entails nearly no cost, as it is based on manuals and courses that need to be implemented, anyway.

Countermeasure 2: Training courses and awareness campaign

A second possibility would be to enhance training course contents to alert about the problem, again with almost no cost as both, the flight and cabin crews, have to participate periodically in such courses. This should be coordinated with an awareness campaign, specially for a/b type personnel, based on flight safety newsletters and reports on flight safety journals. The information reported in these courses should pay special attention to the identified risk, the severity and likelihood of occurrence, the explanation of the actions taken and planned change, and provide feedback on the results of the proposed action proposed. These countermeasures would have a similar moderate effect on all reported causes of incidents, with an estimated cost of EUR 7,000 per year.

Countermeasure 3: Warning devices

We could implement aural and visual warning devices which advice when the slide is still in armed or automatic mode and opening the exit door constitutes a danger. Recently, some infrared sensor detecting movement devices have been tested in some major airlines, with an estimated installation cost of EUR 1,800 per door. The manufacturer declares that these devices would eliminate practically all incidents. However, its reliability is difficult to asses, since this system is not yet standard in the industry. If we consider a 120 aircraft fleet, with 25 wide-bodies (A aircraft type) and 95 narrow-bodies (B aircraft type), it would be necessary to install 728 devices. This entails around EUR 1,300,000 annual. Apart from the investment, a long time would be needed to implement this countermeasure in the whole fleet. Thus, we could check whether they are implemented in all gates (Strategy 1) or only in gates Bf and A1 (Strategy 2). In the second case, the costs have been estimated as EUR 216,000.

Countermeasure 4: Visual reminders

Finally, we could introduce visual reminders close to the operating mechanism, with simple messages such as "Check slide mode before opening door", with an approximate costs of EUR 55 per door. Because of the costs, we could consider two scenarios as before, checking whether they are implemented in all gates (Strategy 1) or only in gates Bf and A1 (Strategy 2). Note also that these devices tend to be fairly effective in the beginning, but not that much in the long run, when people get used to seeing them. Should we implement this countermeasure in all doors and emergency exits, the estimated costs would be around EUR 40,000. Strategy 2 would entail EUR 6,600.

Countermeasure summary

Table 2.8 summarizes the effects of these countermeasures in the reduction of the reported causes of incidents based on expert opinion, implementation cost per unit and total implementation cost for the company. For example, the proposed procedure revision would have negligible costs, would reduce errors by 75%, would not help in reducing non-compliances and, finally, would reduce interruptions by 95%.

Table 2.8: Countermeasure incident reduction and cost.

	Error	Noncomp.	Interr.	Cost/unit	Total cost
Procedure revision	75	0	95	0	0
Awareness campaign	30	30	30	7000	7000
Warning devices, St. 1	99	99	99	1800	1300000
Warning devices, St. 2	99	99	99	1800	216000
Visual reminders, St. 1	20	20	20	55	40000
Visual reminders, St. 2	20	20	20	55	6600

2.3.2 Selection of optimal countermeasures

We describe now how to select the most effective countermeasure, following the framework from Chapter 1. Note that, in our case, incident direct costs will not be affected. Thus, we may only hope to reduce incident frequency with our measures, as described in Table 2.8, and hope to compensate their entailed cost implementation with the reduction in the number of incidents, and, consequently, the corresponding costs.

Since the costs involved are small compared with our airline budget, we assume risk neutrality with respect to the involved amounts and, thus, we shall aim at minimizing expected costs (incident costs plus implementation costs) to compare countermeasures. Based on the cost incident formula (2.2), the general expression for the expected costs per year when we implement countermeasure M is, taking into account the annual 17,000 A operations and 158,000 B operations:

$$\begin{aligned} & 17000(1-q_A^M) \times \left\{ LabE(T_m) + E(C_t) + \left[E(q)E(C^i_{mA}) \right.\right. \\ + \quad & \left.\left. (1-E(q))E(C^e_{mA}) \right] + E(C_d^A)E(T_d^A) \right\} \\ + \quad & 158000(1-q_B^M) \times \left\{ LabE(T_m) + E(C_t) + \left[E(q)E(C^i_{mB}) \right.\right. \\ + \quad & \left.\left. (1-E(q))E(C^e_{mB}) \right] + E(C_d^B)E(T_d^B) \right\} + C^M. \end{aligned}$$

Simple computations lead to

$$\begin{gathered} 17000(1-q_A^M)10501.14 + 158000(1-q_B^M)4378.01 + C^M = \\ 17852380(1-q_A^M) + 691739800(1-q_B^M) + C^M, \end{gathered}$$

where C^M is the implementation cost of the countermeasure, and q_A^M and q_B^M are the proportion of A and B flights in which the incident does not happen, when M is implemented. Similar expressions hold when we consider several year operation spans.

Table 2.9 summarizes the expected net present costs for 1 and 5 years of operations, with a discount factor of 0.98.

Table 2.9: Expected net present costs for 1 and 5 years of operations.

Countermeasure	1 year	5 years
Procedure revision	252902	1214935
Awareness campaign	524477	2492943
Warning devices, St. 1	1307393	1335514
Warning devices, St. 2	616058	2137866
Visual reminders, St. 1	631403	2881078
Visual reminders, St. 2	677329	3228759
None	663400	2224520

Therefore, the most effective countermeasure seems to be the revision of the current procedure. Note, however, that, after five years, the strong investment in warning devices might start to pay off.

We might consider the implementation of several countermeasures simultaneously, in addition to procedure revision. Table 2.10 contains the additional effectiveness of countermeasures, on top of that due to procedure revision, as expressed by our expert.

Table 2.10: Countermeasure effectiveness after procedure revision has been implemented.

	Error	Noncomp.	Interr.
Awareness campaign	0	70	0
Warning devices, St. 1	99	99	99
Warning devices, St. 2	99	99	99
Visual reminders, St. 1	0	10	0
Visual reminders, St. 2	0	10	0

The expected net present costs due to the managed slide deployment for one and five years would now be as in Table 2.11

Table 2.11: Expected net present costs for countermeasures for 1 and 5 years in addition to procedure revision

Countermeasure	1 year	5 years
Awareness campaign	123724	567,739
Warning devices,St. 1	1302,529	1312149
Warning devices, St. 2	352862	873480
Visual reminders, St. 1	273448	1161478
Visual reminders, St. 2	236060	1108918
None	252902	1214935

Note now that the most effective additional measure would be the introduction of awareness campaigns. All in all, in 5 years we are able to reduce expected costs from EUR 2.3 million to EUR 0.6 million with simple yet effective measures.

2.4 Discussion

Unintentional slide deployment is a main cabin safety issue that has non-negligible costs for commercial airlines, specially within an increasing competition context. As an example of its relevance, a manufacturer has developed an innovative audible alert system that could mitigate such threat considerably, by warning crew when an exit or emergency door is open in case it should not.

We have provided here a detailed risk analysis for such problem for a major airline, assessing several factors that could potentially affect this event, identifying potential countermeasures, some of then as simple conceptually as a procedure revision and risk communication, and providing a simple and cost effective solution. Although aviation incidents and accidents are commonly a result of several contributing factors, human error is recognized as their main cause worldwide. Furthermore, implementing only one countermeasure is rarely sufficient to avoid an incident or accident to occur. Thus, we have proposed not only technical solutions but also procedure revisions as countermeasures.

The incumbent company has implemented our proposed measures. In spite of this type of technical study, implementing the actual decision was not easy because of the usual resistance to change. The company actually had to undertake a communication campaign at various decision making levels, including managers, instructors and other airline professionals, to make the company aware of the current and potential effects of this incident. Such documents translated the incident and its entailed risks into a non-technical language with which decision makers could relate with, understand and incorporate into their decisions. We followed the suggestions by ICAO (2009) addressing in a targeted way: the management which was informed of the potential losses to the organization; crews which had to change their procedures were informed of the hazards and rationale for the action being taken; and personnel type a/b was specially informed of the severity and likelihood of occurrence of the hazard. Indeed, after a period of 6 months elapsed since that decision was made, the number of deployments has been 4 vs 18 to 24 which would be expected had we not had managed such risks.

There are many other relevant risks, specially in the same flight phase (aircraft boarding and loading and taxiing), that might benefit from an approach similar to the one described here. Though only 0.1 % of aviation fatalities occur during these flight phases, statistics indicate that around 8% of accidents occur during this phase. An example of this is ground damage events in which an aircraft is damaged by ground equipment. Another one is the fueling for holding decision which is the object of Chapter 3.

Chapter 3

Fuel for Holding for Arriving Aircrafts at Congested Airports

3.1 Introduction

Today's competitive environment is forcing airlines to reduce operating costs. This might eventually affect safety, which is a critical factor in the aviation industry. According to IATA, fueling is one of the major Direct Operating Costs (DOC) for air carriers, typically 30%, which aim at reducing their impact by improving fuel efficiency, see Vasigh et al. (2008). As an example, in 2008 fuel represented the greatest share of airline costs due to the record high prices of oil experienced that year. Thus, Airline Flight Operations Departments are trying to reduce fuel consumption, while keeping safety as a top priority. On the other hand, just in Europe, around 750,000 flights in 2009 had some Air Traffic Flow Management (ATFM) delay, with an estimated total cost of EUR 1,250 million, see Cook and Tanner (2011). In 2012, the Central Office for Delay Analysis (CODA) reported that 34% of flights were delayed by 5 minutes or more on arrival, with an average delay, per delayed flight, of 28 minutes. 2012 delays remained at a stable level compared to 2011.

We provide here a decision analysis model to support the Flight Operations and Dispatch decision of how much extra fuel to include for holding at destination. Although there are many significant factors that could affect this decision, we shall only consider holdings due to ATFM delays. From the point of view of air transportation companies, the standard current approach to such decisions is to fuel aircrafts with an estimated additional fuel quantity if there is information about delays at destination, without modeling and assessing potential costs, such as those related with diverting. Such costs may be particularly significant for those airlines with hub-and-spoke distribution models rather than point-to-point route networks. Cook et al. (2009) and Ferguson et al. (2012) provide recent reviews on the topic.

We first describe the general approach to fueling a flight for holding. Then, we provide a general continuous decision tree for such problem and its general solution. We next describe the solution for a specific case at a major international airport, comparing our solution with the approach currently in force, showing the relevance of our framework. We end up with some discussion.

3.2 The fueling for holding problem

The amount of fuel required for flying a planned route is calculated for each flight according to the specific policy of each operator, based on regulatory requirements, established by different national and international legislations, see, e.g., EASA (2008). Such policy should ensure that every flight carries sufficient fuel on board for the planned operation as well as a reserve to cover deviations due to factors such as poor weather, runway unavailability or delays due to traffic congestion. As an example, a wide body aircraft flying between Europe and America should be dispatched with approximately 1.5 tons of additional fuel to be able to hold for 15 minutes at destination. This would cost roughly EUR 71,000 per route yearly to the airline.

When delays occur during the approach flight phase, holding may be required by Air Traffic Controllers (ATC) forcing the crew to fly according to a predetermined maneuver called "holding pattern", which keeps the aircraft within a specified airspace, while awaiting further clearance from ATC, see FAA (2008a). The standard holding pattern uses right-hand turns and takes approximately 4 minutes to complete: one minute for each 180 degree turn and two one-minute outbound and inbound straight ahead legs, see Figure 3.1.

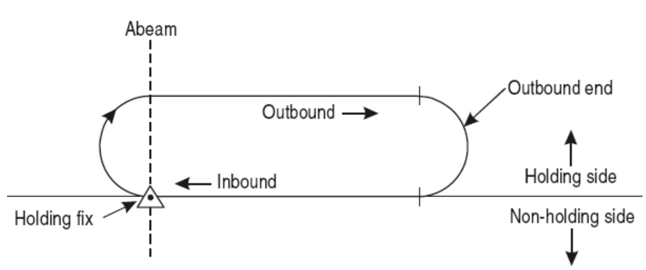


Figure 3.1: Holding pattern right turn. Source: ICAO (2006a)

The crew will be able to hold depending on the remaining quantity of fuel. Inability to hold because of a fuel shortage will cause the flight to divert to an alternate airport. During the holding flight phase, when the available fuel on board is approaching to the amount of fuel necessary to fly to the alternate airport, the crew must make a decision between remaining on the holding pattern or diverting to the alternate. This is not a simple decision as it entails serious inconveniences for passengers, as well as significant DOC for the company, including additional fuel burnt, maintenance costs, extra handling bills, extra ATC charges and flight and cabin crew costs. As an example, a wide body aircraft diverted at destination would entail around EUR 22,500 in additional DOC. Moreover, when a diversion to an alternate airport occurs, this typically has a "knock-on" effect on other aircrafts, and the delay may propagate through the network until the end of that operational day, leading to considerable additional costs.

One of the main reasons for holding is traffic congestion on approach. In 2009, CODA reported that 39% of the busiest arrival airports in Europe had an average delay per movement of more than 10 minutes. This operating environment entailed 748,830 delayed flights distributed as in Figure 3.2.

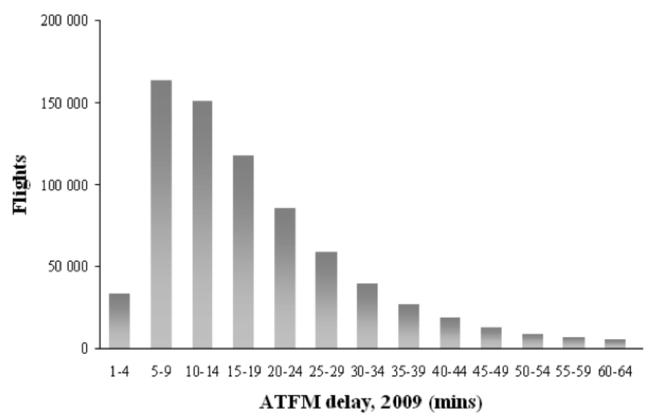


Figure 3.2: 2009 ATFM delay in minutes. Source: Cook and Tanner (2011)

To further stress the relevance of this phenomenon, some figures regarding European ATFM delay costs in 2010 may be illustrative: it entailed EUR 1,250 million in total costs, with an average cost of EUR 1,660 per ATFM delayed flight, see Cook and Tanner (2011) for further details. From the airline company perspective, although total delay costs comprise several components, they are often dominated by passenger costs, see Cook and Tanner (2009). Furthermore, passenger services and re-accommodations are rarely integrated with Flight Operations, and each department typically operates under its own regulations, with their own budget and performance measures, see Kohl et al. (2007) and Clausen et al. (2010). Most airlines are not deeply integrated and this usually entails that different working teams trying to do their individual best could actually be competing against each other.

Thus, deciding how much fuel to carry on for holding at destination due to delays has become an important issue given the increasingly frequent busy airports. On one hand, as mentioned before, a deviation to the alternate airport entails significant costs to the airline. On the other, aircrafts should carry enough fuel to avoid diversions caused by ATFM delays, but this could have a significant impact, given that fuel represented about 32.2% of the total operating costs in 2008, as reported by IATA (2010). Moreover, a modern aircraft burns between 3% to 4% of additional fuel carried per hour of flight, just to carry such fuel, known as the Fuel Carriage Penalty (FCP). As an example, a standard transatlantic flight from Europe to America, which boards 5,000 kg of extra fuel, will burn about 1,300 kg of that fuel simply to carry it. Therefore, excessive fuel on board at destination may have a considerable impact in the profit and loss account of a company. As a consequence, companies are putting pressure on flight crews to reduce fuel consumption, in some cases to an extreme. IATA suggests that a mere 1% saving in fuel consumption for a medium aircraft saves about 100 tons of fuel annually, inducing an approximate annual cost reduction of EUR 38,000 per aircraft. In addition, such saving would also reduce emissions considerably, an increasingly important issue for companies and governments, see SITA (2007) for details.

Under these limitations, a good understanding of this problem and its consequences can help airlines not only to operate fuel more efficiently, and possibly save money, but also to better deal with low fuel events, entailing safer flights. An airline's fuel cost per available seat mile is a result of two factors: the price of fuel and the fuel efficiency. Although the price of fuel is generally beyond the airline's control, the airline can lessen the impact of such cost by using more complex fuel efficient flight planning strategies, in which fuel for holding decisions play a major role. Current flight planning systems and aircraft performance monitoring allow companies to have fairly efficient flight plans. However, fuel shortages do still occur mainly, and increasingly, due to excessive holding time delays.

A fuel shortage is defined as a situation in which fuel on board may not be sufficient to reach the final destination with the final reserve fuel, that is, the minimum fuel required to fly at a holding speed for 30 minutes at 1,500 feet above the alternate airport, or the destination airport if an alternate is not required, in the so-called International Standard Atmosphere (ISA) conditions, see Kermode et al. (2006).

In such competitive scenario, a decision-making model is needed to evaluate the benefits and costs for a proposed holding fueling policy adopted by an airline. Applying it consistently, an airline could find a break-even point at which constantly carrying extra fuel for holding in congested terminal areas is less costly than a too frequent diversion to an alternate airport. Sometimes, crews report this problem at specific airports. Then, the corresponding Airline Flight Operations Division should analyze the issue in order to know where and how often diversions happen, how long holdings tend to be and how much additional fuel is burnt. Once these issues have been analyzed, Flight Operations should assess diversion costs and risks, and determine how much holding fuel to board, possibly as we suggest.

3.3 A decision model for the fuel for holding problem

Essentially, an airline decision-making process to come out with how much fuel should be loaded for holding would be typically done based on a forecast for the ATFM delay. To model the problem two variables could be considered: fuel holding quantity or holding time. Fuel consumption depends on many factors such as the aircraft model, gross weight, distance, altitude, speed, temperature or wind. To reduce model complexity, we shall use holding time as our decision variable. Once the holding time has been decided, the Flight Planning System will be able to compute the fuel for a specific route, aircraft or weight under various proposed conditions.

When an airplane is approaching its destination, it could be required to hold for a certain time, should there be some ATFM delay. Depending on that, and the amount of fuel available, the flight might need to divert. This entails some economic consequences that can be expressed mainly through the following DOC:

- Fuel costs, including the FCP, which will depend on the flight time. It covers fuel consumption while the aircraft is flying in the holding pattern and the fuel burnt due to the additional flight time as a consequence of the diversion.
- Maintenance costs due to delay, based on factors such as the mechanical attrition of aircrafts waiting at gates or aircrafts accepting longer re-routes to obtain a better departure time (slot).
- Handling costs, as diversion to the alternate airport means additional handling services to the aircraft.
- Air Traffic Services (ATS) charges. These costs are due to another approach and landing required, together with another takeoff to fly back to the original destination.
- Crew costs, mainly due to the increased flight time.
- Other costs, including passenger costs. As described in Cook and Tanner (2011), these may be classified as *hard* or *soft*. Hard costs refer to factors such

as passenger rebooking, compensation and care. Soft costs are more difficult to quantify, but they manifest in several ways. For example, if a flight is delayed, a passenger with a flexible ticket may decide to take a competitor's on-time flight, instead of the one in which he was originally booked. As a result of dissatisfaction, he might not travel again with this airline. There is almost no literature concerning passenger soft costs, an issue which remains poorly understood.

In our decision model, we shall consider that the following scenarios may take place:

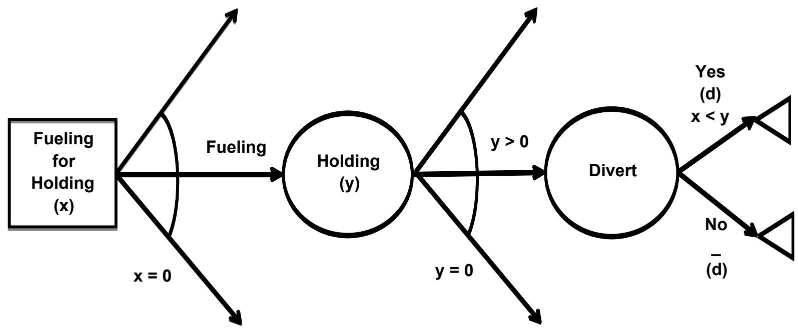
1. In case of fueling for holding, but not sufficiently to cope with the delay, the flight will need to divert. The consequences in DOC would be:
   (a) FCP costs, due to fueling for holding.
   (b) Burnt fuel costs, from the holding point to the alternate airport and flying back to destination.
   (c) Maintenance extra time costs.
   (d) Handling costs.
   (e) ATS costs.
   (f) Crew costs.
   (g) Soft costs, such as passenger costs.
2. In case of fueling for holding sufficiently to cope with the delay time, the flight will not need to divert. The relevant consequences in DOC would be (a), the burnt fuel costs due to fuel consumption during holding, (c), (f) and (g).
3. In case of fueling for holding, but there being no delay, the consequences would just be the FCP costs.
4. In case of not fueling for holding and the flight is delayed, it will be necessary to divert. The consequences in DOC would be the same as in Case 1, except for the FCP costs.
5. In case of not fueling for holding and the flight is not delayed, there would be no additional DOC.

Note that we have simplified our model by considering that, when a flight is requested to hold but there is not fuel for holding on board, the crew proceeds to diverting without delay to the alternate airport.

3.3.1 A decision tree for the fueling for holding problem

We shall structure the fueling for holding problem with the aid of a continuous decision tree, shown in Figure 3.3, and depicted from the perspective of the company.

Figure 3.3: Fuel for holding continuous decision tree.



Therefore, it refers to the problem in general, and not in relation with a specific flight with a specific crew.

We formalize the problem. The airline has to decide how much fuel, x (measured in holding time), must be loaded in an aircraft to possibly cope with a holding operation. On approaching destination, if there is some ATFM delay time y, the aircraft will have to hold. We have a forecasting model for y. With nonzero probability p, there will be no delay, i.e., $Pr(y = 0) = p$, the flight is not required to hold and it will be able to land as scheduled. Conditional on $y > 0$, the required holding time will be distributed with density $f(y)$. When $y \leq x$, i.e. the fuel x for holding time on board is sufficient to deal with the delay time y, the aircraft just flies into the holding pattern for such time y. Then, it proceeds to the original scheduled destination without needing to divert ($\bar{d}$) to the alternate airport, but arriving after the scheduled time. Finally, when $y > x$, the aircraft is not able to hold, and it needs to divert (d). Table 3.1 summarizes the additional operating costs for our five cases, in terms of x and y, measured in minutes.

Table 3.1: Consequences in the fuel for holding problem.

Case	x	y	FCP	Delay holding costs	Diversion + handling costs
1	$x > 0$	$y > x$	Yes	No	Yes
2	$x > 0$	$y \leq x$	Yes	Yes	No
3	$x > 0$	$y = 0$	Yes	No	No
4	$x = 0$	$y > x = 0$	No	No	Yes
5	$x = 0$	$y = 0$	No	No	No

3.3.2 Modeling costs

As discussed above, the consequences in relation with the fuel for holding problem can all be largely monitored. We model now the relevant costs qualitatively described in Table 3.1, which are:

- Diversion costs, $C_{Diversion}$ (plus handling costs);
- Delay holding costs, $C_{Holding}$;
- Fuel carriage penalty costs, C_{FCP}.

Diversion costs

To identify and assess the costs $C_{Diversion}$, associated with diverting to the alternate airport and flying back to the original destination, we consider three legs in such operation:

1. Costs related with proceeding from the holding point to the alternate airport, which we call *En-Route Phase 1 Delay Cost*, C_1.
2. Costs related with turnaround at the alternate airport, which we call *At-Gate Phase 2 Delay Cost*, C_2. Here, we shall include also the handling costs, $C_{Handling}$, which may be assumed fixed for each type of airplane, as we illustrate in Section 3.4.4.
3. Costs related with proceeding from the alternate airport to the original destination, which we call *En-Route Phase 3 Delay Cost*, C_3.

Therefore, we obtain the total diversion costs by adding the three phase costs:

$$C_{Diversion} = C_1 + (C_2 + C_{Handling}) + C_3.$$

The C_i terms will depend on the time spent at the corresponding legs. To estimate such times (t_1, t_2 and t_3) for a given airport, we may use judgmental elicitation, asking an expert to provide assessments for the minimum (LQ), the maximum (UQ) and the most likely (Mode) time delays at each phase. Then, we may apply the methodology in Galway (2007). To mitigate expert overconfidence, we shall assume a triangular distribution with 0.05 and 0.95 quantiles at the minimum and the maximum provided by the expert. We provide an example in Section 3.4.4.

In order to estimate the costs in relation with such times, we base our calculations on Cook and Tanner (2011). They provide a model for full tactical (fuel, maintenance, crew, pax) costs ($dcost$) in EUR versus the square root of the aircraft Maximum Take Off Weight (MTOW), for both the At-gate and En-route flight phases, which take the form

$$dcost = m \cdot \sqrt{MTOW} + c,$$

where m and c depend on the delay, as shown in Table 3.2. Since these calculations

Table 3.2: Coefficients for full tactical cost *vs* $\sqrt{MTOW}$, Cook and Tanner (2011).

t (mins)	5	15	30	60	90	120	180	240	300
				En-route regression coefficients					
m	42.9	163	443	1599	3907	8104	11683	14408	17614
c	-147	-524	-1348	-4801	-11367	-27759	-42551	-47809	-52793
				At-gate regression coefficients					
m	12.5	71.6	260	1233	3358	7371	10583	12942	15781
c	-32.9	-178	-663	-3432	-9315	-25015	-38440	-42327	-45932

are only available for a few specific delay times, $t_1 = 5, \ldots, t_D = 300$, we shall fit the m and c coefficients for appropriate nonlinear models. As an example, Figure 3.4 reflects the m coefficient for phases 1 and 3 *vs* the corresponding delay times, suggesting a nonlinear regression model for the En-route phase m coefficients.

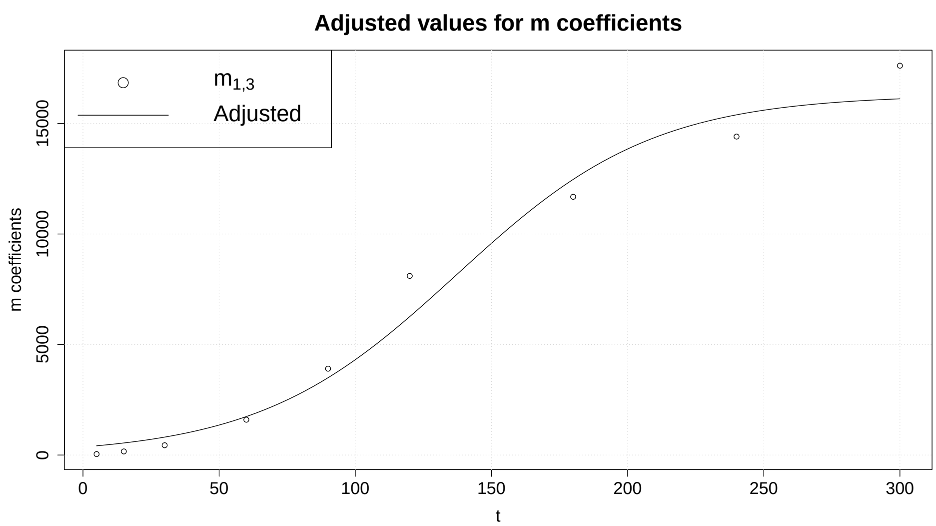


Figure 3.4: m coefficients *vs* delay fitted with a nonlinear regression model.

We have estimated a logistic growth curve model, where the data available for the m coefficient follow a normal distribution with variance σ^2

$$m_j \sim \mathcal{N}(\eta_j, \sigma^2),\ j = 1, \ldots, D,$$

whose mean η_j depends on t_j, the delay at which m_j has been recorded, through

$$\eta_j = \frac{\lambda_1}{1 + \exp\left[-\lambda_2 \cdot (t_j - \lambda_3)\right]}.$$

We have used relatively flat priors for the parameters $\lambda_1, \lambda_2, \lambda_3$, and σ^2. We have fitted similar models for the parameters m_2, $c_{1,3}$ and c_2. Table 3.3 provides posterior estimates and variances for the relevant parameters of such models, obtained with the aid of WinBUGS (Lunn et al., 2000), as with other models estimated throughout this Chapter. The plug-in estimate curves for the m and c coefficients would be

Table 3.3: Posterior means and variances of the parameters of the model for diversion costs.

	λ_1	sd	λ_2	sd	λ_3	sd	σ^2	sd
$m_{1,3}$	16297.70	1051.28	0.028	0.0050	137.12	15.23	1060.91	218.78
m_2	15076.74	1109.55	0.027	0.0051	140.61	15.01	1051.05	218.63
$c_{1,3}$	−49126.83	1511.66	−0.042	0.0056	121.21	9.93	2016.83	438.86
c_2	−43836.56	1417.20	−0.042	0.0056	120.81	10.01	1998.12	448.78

$$\begin{aligned}
m_i(t_i) &= \frac{16297.70}{1 + \exp\left[-0.028 \cdot (t_i - 137.12)\right]}, \; i = 1, 3, \\
m_2(t_2) &= \frac{15076.74}{1 + \exp\left[-0.027 \cdot (t_2 - 140.61)\right]}, \\
c_i(t_i) &= \frac{-49126.83}{1 + \exp\left[0.042 \cdot (t_i - 121.21)\right]}, \; i = 1, 3, \\
c_2(t_2) &= \frac{-43836.56}{1 + \exp\left[0.042 \cdot (t_2 - 120.81)\right]}.
\end{aligned}$$

Then, in general, for a delay t_i we shall write

$$C_i(t_i) = m_i(t_i) \cdot \sqrt{MTOW} + c_i(t_i), \; i = 1, 2, 3.$$

Finally, by substituting the delay random costs, we get the following predictive distribution for the diversion costs

$$C_{Diversion} = C_1(t_1) + C_2(t_2) + C_3(t_3) + C_{Handling}.$$

Delay holding costs

We have adopted the previous strategy for the estimation of the delay holding costs, considering that the flight is incurring in an "En-route delay". Therefore, the delay holding related costs adopt the following distribution, which depends on the holding time y,

$$C_{Holding} = C_1(y).$$

Fuel carriage penalty costs

We provide now a model for the FCP. As an example, a short/medium haul aircraft flying a typical 2.5 hours route could increase the burnt fuel between 50 kg to 70 kg per each 1,000 kg of additional fuel loaded. For a given flight, this consumption may depend on several variables that we have explored, including aircraft type, factors affecting the increased drag due to poor airframe conditions and engine deterioration performance, average outside air temperature, average wind component, aircraft weight or flight time, among others. We have obtained an excellent fit when explaining FCP based on flight time for different aircraft types (AT), based on

$$\text{FCP}(t_{\text{Flight time}}) = a + b \cdot t_{\text{Flight time}}, \tag{3.1}$$

where FCP(%) is expressed as a percentage (extra fuel burnt per additional 100 kg fuel loaded), and $t_{\text{Flight time}}$ is measured in minutes, being its value

- $t_{\text{std}} + y$, if the flight does not need to divert, or
- $t_{\text{std}} + t_1$, otherwise,

where t_{std} is the standard duration of the flight. We have available 42, 38, 28, 23 and 24 $(\text{FCP}, t_{\text{Flight time}})$ observations, recorded in 2011, for the five types of aircraft considered, respectively.

We use a hierarchical linear model to capture the differences between various types of aircrafts. Let us denote by F_{ij} the j-th available FCP for the i-th aircraft type, $i \in \{\text{A}, \text{B}, \text{C}, \text{D}, \text{E}\}$. We assume that F_{ij} follows the model

$$F_{ij} \sim \mathcal{N}(a_i + b_i \cdot t_{ij}, \sigma_F^2),$$

where t_{ij} is the j-th available flight time for aircraft i, and σ_F^2 is the variance, which we assume equal for all times and aircraft types. Besides, we also assume relatively diffuse normal priors on the a's and b's,

$$a_i \sim \mathcal{N}(a_0, \sigma_a^2),\ b_i \sim \mathcal{N}(b_0, \sigma_b^2),\ i \in \{\text{A}, \text{B}, \text{C}, \text{D}, \text{E}\}.$$

We also consider a relatively diffuse prior for σ_F^2. Table 3.4 summarizes the posterior means of intercepts and slopes. We have plotted in Figure 3.5 the scatterplot for each aircraft type, together with the corresponding regression line, resulting from plugging the posterior estimates of Table 3.4 into (3.1).

Finally, the FCP costs (C_{FCP}) related with the holding fuel loaded would be

$$C_{\text{FCP}}(t_{\text{Flight time}}) = \text{FCP}(t_{\text{Flight time}}) \cdot x \cdot \text{Fuel unit cost}.$$

Table 3.4: Posterior means of intercepts and slopes

AT	A		B		C		D		E	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
Intercept	-0.821	0.397	-1.085	0.510	-1.622	0.716	-2.617	0.62	-4.736	1.536
Slope	0.042	0.0026	0.048	0.0053	0.053	0.0064	0.043	0.0018	0.043	0.0028

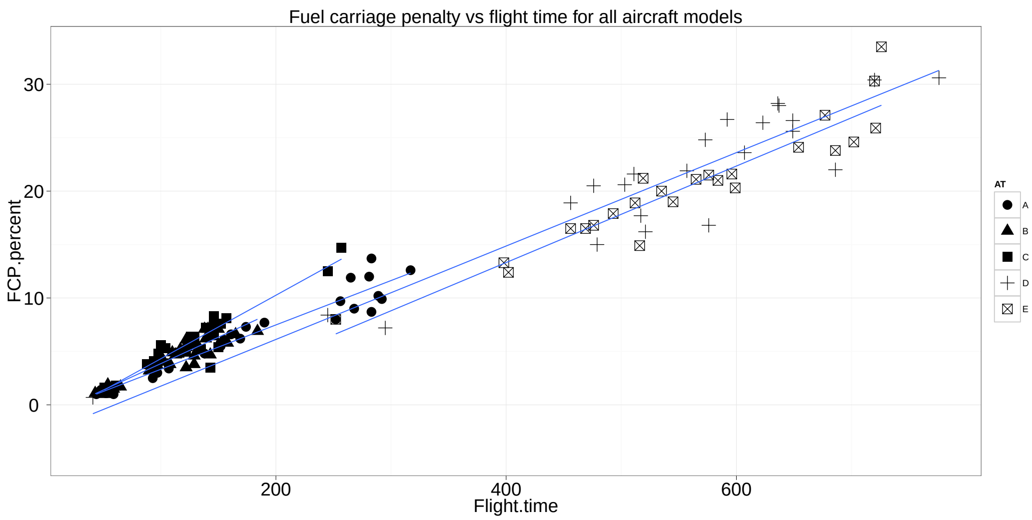


Figure 3.5: Fuel carriage penalty *vs* flight time.

3.3.3 Maximum expected utility for the fueling for holding problem

Let us denote by $u(x, y, d)$ the utility associated with the costs that are incurred when x is our fueling for holding decision, y is the holding time, and d refers to whether we have to divert or not. Then, we would need to solve the following problem

$$\max_{x \geq 0} \psi(x) = \int \Big\{ p \cdot u(x, 0, \bar{d}) + (1-p) \Big[\int_{y \leq x} f(y) u(x, y, \bar{d}) dy + \int_{y > x} f(y) u(x, y, d) dy \Big] \Big\} g(p) dp,$$

where $g(p)$ designates the density over the probability p of not having to hold. This would provide us with the optimal amount of fuel for holding to be loaded on the aircraft.

Typically, we shall need to approximate the objective function by Monte Carlo through

$$\hat{\psi}(x) = E(p) \cdot u(x, 0, \bar{d}) + [1 - E(p)] \left[\frac{\sum_{y_i \le x} u(x, y_i, \bar{d}) + \sum_{y_i > x} u(x, y_i, d)}{N} \right], \tag{3.2}$$

being $\{y_i\}_{i=1}^N$ a sample from $f(y)$, the density of $Y|y > 0$.

To proceed with the optimization, we have that $x \in [0, T]$, where T is the maximum reasonable holding time. Since ψ is costly to evaluate, we shall use a regression metamodel approach, see e.g. Barton and Meckesheimer (2006). For that, we choose a few points $(x_1, x_2, \ldots, x_r) \in [0, T]$, approximate $\psi(x_i)$ by Monte Carlo through $\hat{\psi}(x_i)$, and fit a regression model to $\{(x_i, \hat{\psi}(x_i))\}$, which we call $\bar{\psi}(x)$. We, then, solve the univariate nonlinear bound-constrained problem

$$\begin{array}{ll} \max\limits_{x} & \bar{\psi}(x) \\ \text{s.t.} & x \in [0, T]. \end{array}$$

We discuss now several implementation details through a case study.

3.4 A case study

We shall consider operations at a major European international airport where delays due to the ATFM factor are very important for a major airline. In this scenario, the company must decide how much additional fuel should be loaded in their flights arriving to this airport to cope with ATFM delays and mitigate diverting to the alternate due to delays on arrival. As an example, the relevant airline undertook 77,521 arrivals in the incumbent airport over a year, with 11 diversions to alternate airports due to delays on approach out of 4,388 delayed operations.

3.4.1 Probability of holding

The first relevant source of uncertainty in the problem is the probability of not having to hold, which we have designated $p = Pr(Y = 0)$. For this, we shall use a simple beta-binomial model, see e.g. French and Ríos Insua (2000), with

$$p \sim \beta e(1, 1),$$

$$S \sim Bin(n, p),$$

where S designates the number of operations not having to hold over n operations. We use a non-informative prior since the number of operations is very high, thus rendering prior information of little relevance. Then, a posteriori,

$$p|data \sim \beta e(1+s, 1+n-s).$$

When necessary, we shall estimate such probability through the posterior expectation

$$\hat{p} = \frac{1+s}{2+n}.$$

In our case, with $s = 73133$ (and $n = 77521$),

$$p|data \sim \beta e(73134, 4389),$$

and, when necessary, we shall set

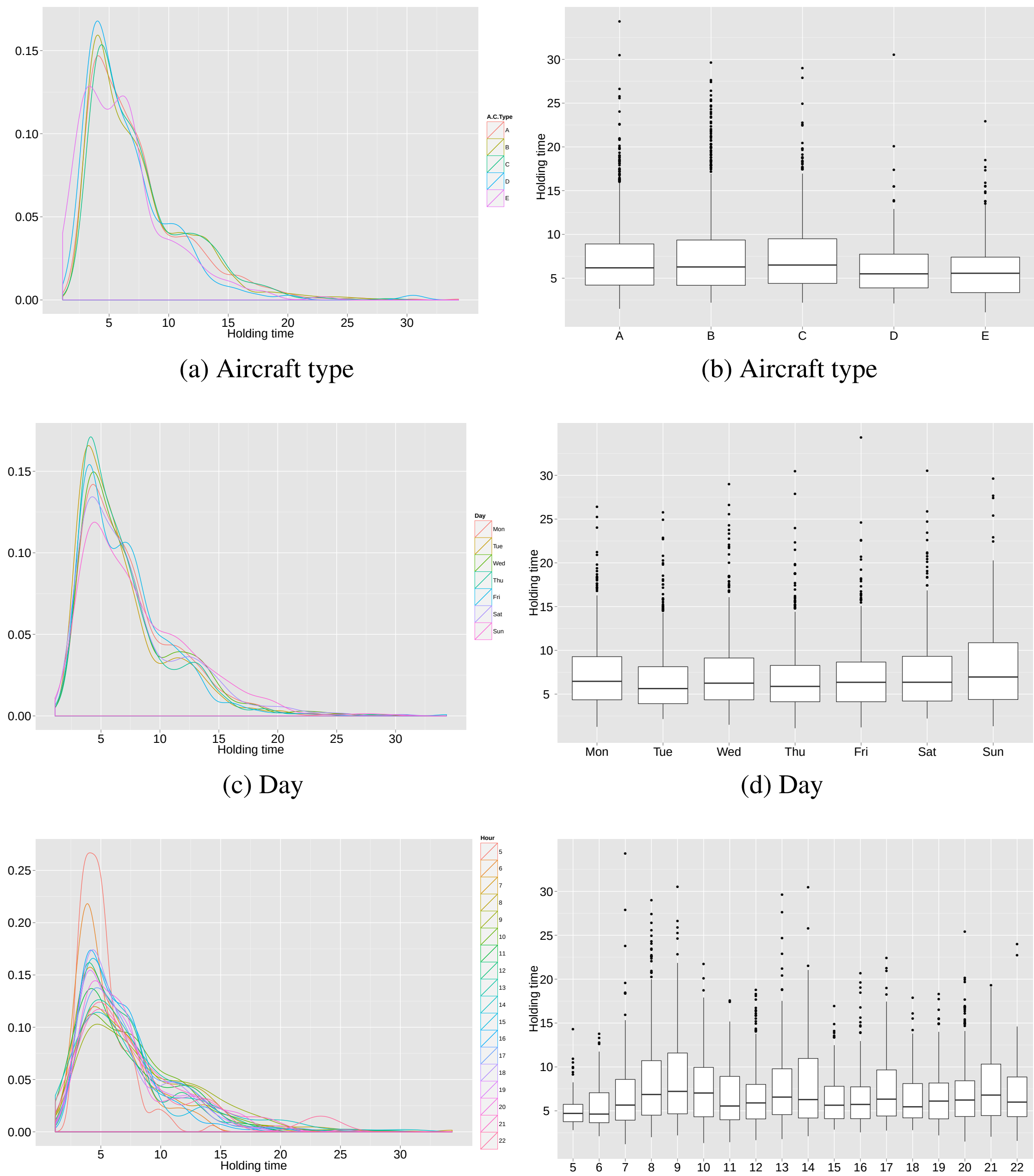
$$\hat{p} \simeq 0.9434.$$

3.4.2 Modeling holding times

We discuss now the assessment of the holding time distribution, conditional on it being positive. For this, we have available 4,388 observations referring to 12 months of operations, where we only consider delays induced in the controlled airspace surrounding a major airport when holding in a standard pattern, see Figure 3.1.

In an attempt to identify possible factors affecting holding delays, Figure 3.6 provide kernel density estimates and boxplots for holding times, grouped according to *Aircraft type* (Figures 3.6a–3.6b), *Day of the week* (Figures 3.6c–3.6d), and *Hour of day (24 hours)* (Figures 3.6e–3.6f). In the latter, we do not include those hour segments in which less than five operations were registered.

The day of operation and the type of aircraft seem to have little effect on the holding time. However, the arrival hour seems very influential, in consonance with the busiest times at the incumbent airport (early morning, midday and late evening). Therefore, we shall take this fact into account in our model.



(a) Aircraft type (b) Aircraft type

(c) Day (d) Day

(e) Hour (f) Hour

Figure 3.6: Holding time densities and boxplots.

Figure 3.7 provides the histogram for the whole data set of delays, with an overlaid kernel density estimate which suggests a mixture model for the holding time.

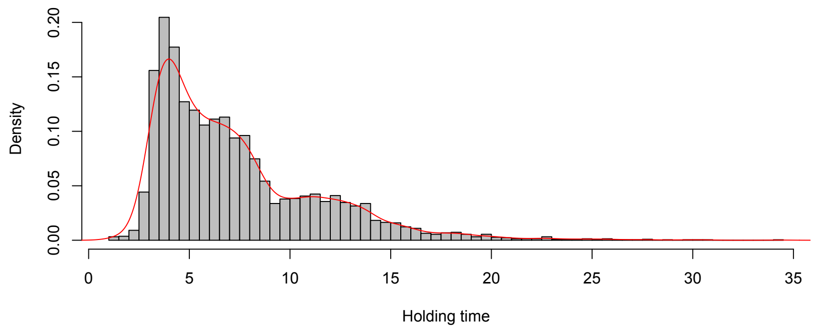


Figure 3.7: Holding time histogram.

This is also apparent in Figure 3.6, in which mixture models seem relevant as well. This agrees with the physical description of the holding operation, as airplanes will typically fly an integer number of holdings before effectively starting the approach flight phase. Moreover, the number of holdings will rarely go beyond four. Indeed, we can only observe one extreme holding time value of over 34 minutes, and four apparent components in the mixture.

As we are dealing with positive data (times), we shall adopt the gamma mixture model approach in Wiper et al. (2001), with four mixture components: we shall consider that non-zero holding times will follow the model

$$f(y|w, \mu, \nu) = \sum_{i=1}^{4} w_i \mathcal{G}(y|\nu_i, \nu_i/\mu_i),$$

with

$$\mathcal{G}(y|\nu_i, \nu_i/\mu_i) = \frac{(\nu_i/\mu_i)^{\nu_i}}{\Gamma(\nu_i)} y^{\nu_i - 1} \exp\left(-\frac{\nu_i}{\mu_i} y\right),$$

where $w_i \geq 0$ are the mixture weights, with $\sum_{i=1}^{4} w_i = 1$. Our parametrization of the gamma densities are in terms of their means, μ_i, and shape parameters, ν_i. We assume also the prior model:

$$\begin{array}{lcll} w & \sim & \mathcal{D}(\phi), & \text{a Dirichlet distribution,} \\ \nu_i & \sim & \mathcal{E}(\theta), & \text{an exponential distribution, for } i = 1, \ldots, 4, \\ \mu_i & \sim & \mathcal{IG}(\alpha, \beta), & \text{an inverted gamma distribution, for } i = 1, \ldots, 4, \end{array}$$

with $w = (w_1, w_2, w_3, w_4)$, and the restriction $\mu_1 < \cdots < \mu_4$ to ensure identifiability of the posterior distribution. We set $\phi = 1$ to give a uniform prior over weights, and $\theta = .01$, $\alpha = 1$ and $\beta = 1$, to attain relatively diffuse priors.

Table 3.5 shows the posterior estimates of the parameters (ν_i, μ_i) and weights $w_i,\ i = 1, \ldots, 4$ when the whole data set of delays is considered. In Table 3.6, we

Table 3.5: Gamma mixture components for all times

	Component 1			Component 2			Component 3			Component 4		
	ν_1	μ_1	w_1	ν_2	μ_2	w_2	ν_3	μ_3	w_3	ν_4	μ_4	w_4
All times	25.88	4.05	0.39	32.60	6.90	0.32	28.02	11.85	0.19	5.65	13.15	0.11

have grouped the results according to the landing time, taking into account only those 1-hour periods with more than 5 holding operations. From Tables 3.5 and 3.6,

Table 3.6: Gamma mixture components for different hours

	Component 1			Component 2			Component 3			Component 4		
Hour	ν_1	μ_1	w_1	ν_2	μ_2	w_2	ν_3	μ_3	w_3	ν_4	μ_4	w_4
5	98.32	3.47	0.27	71.01	4.65	0.32	67.66	6.16	0.24	25.97	12.95	0.17
6	52.20	3.26	0.37	56.32	5.64	0.31	55.74	7.85	0.22	83.89	11.64	0.10
7	21.55	3.94	0.44	73.40	6.54	0.22	16.85	10.70	0.30	39.44	27.77	0.04
8	43.03	3.82	0.25	14.90	7.03	0.49	55.82	12.72	0.20	32.45	19.97	0.06
9	21.66	4.12	0.32	62.27	7.07	0.23	28.84	12.05	0.29	32.36	18.44	0.16
10	17.14	4.07	0.37	82.19	7.33	0.24	84.02	9.96	0.12	18.30	12.71	0.27
11	67.27	2.48	0.21	34.58	5.48	0.34	55.51	8.33	0.18	33.44	12.26	0.27
12	47.19	3.31	0.29	46.37	5.67	0.32	89.97	8.76	0.25	41.51	13.21	0.14
13	13.53	4.60	0.40	31.46	7.79	0.35	45.41	12.56	0.22	54.05	23.50	0.03
14	17.96	4.15	0.46	97.60	7.02	0.21	59.96	12.57	0.2	31.96	24.35	0.13
15	47.24	3.95	0.36	53.48	6.18	0.29	66.22	8.66	0.24	65.18	16.60	0.11
16	35.64	3.92	0.35	44.08	6.51	0.33	36.36	9.22	0.25	52.41	15.76	0.06
17	40.71	3.96	0.29	23.63	6.61	0.44	40.37	11.75	0.24	74.80	18.59	0.04
18	68.68	3.79	0.29	45.31	5.55	0.34	70.46	9.10	0.20	42.81	12.95	0.16
19	39.93	3.62	0.28	55.67	5.55	0.27	42.09	8.13	0.26	30.39	24.27	0.20
20	12.57	4.70	0.53	109.28	7.18	0.19	65.19	11.32	0.13	26.89	18.64	0.15
21	30.41	4.00	0.31	66.36	6.52	0.24	56.39	9.63	0.22	47.58	14.58	0.22
22	122.60	1.64	0.08	27.34	5.33	0.52	65.41	10.62	0.23	73.97	24.90	0.17

we appreciate that the model captures nicely the physical process of the holding operation, with at most four holding turns and taking around four minutes per holding. We can also appreciate the changes in mixture weights and means in the model when we consider hourly delays, clearly suggesting the need to take into account the arrival hour, as delays depend on that.

3.4.3 Modeling diversion times

As described in Section 3.3.2, in case of diversion to the alternate airport due to significant delays, we have estimated the time spent using judgmental elicitation asking an expert. We assume triangular distributions with 0.05 and 0.95 quantiles in the minimum and the maximum. Table 3.7 shows the relevant information for the incumbent distributions.

Table 3.7: Parameters of the triangular distributions for delay times

Phase	Min	LQ	Mode	UQ	Max
t_1	16.10	20.00	30.00	35.00	37.95
t_2	18.22	30.00	50.00	90.00	105.60
t_3	31.10	35.00	45.00	50.00	52.95

3.4.4 Optimization

We proceed now with optimization. We initially assume risk neutrality in costs, as costs in relation with holding operations are small in comparison with the airline budget. Thus, we aim at minimizing expected costs. We shall consider two cases operating at the incumbent airport,

- A long-haul flight which operates with an "E" wide-body aircraft.
- A short-haul flight which operates with an "A" narrow-body aircraft.

In both cases, the fuel cost is assumed to be 0.60 EUR/kg.

Long-haul flight

In the first case, a wide-body type "E" aircraft ($\sqrt{MTOW} = 19.18$ and $C_{Handling}$ = EUR 3,500) arrives at the incumbent airport. We shall determine the optimal fuel for holding, depending on the arrival time. Let us first consider that the flight approaches the destination airport at 09:00 Local Time (LT) after 9 hours and 35 minutes of flight time (t_{std}). The aircraft was actually dispatched at the departing airport with 2,490 kg of fuel for holding 20 minutes at destination in case of ATFM delays. We allow for a maximum reasonable holding time of $T = 60$ minutes, and divide the interval $[0, T]$ in $M = 120$ subintervals of length $l = T/M = 30$ s. We undertake a Monte Carlo approximation (3.2) at each of the times with $N = 30,000$. Figure 3.8 provides the expected cost fitted, which we have approximated with a polynomial regression metamodel with $R^2 = 0.99$.

The minimum of the adjusted metamodel was at $x^* = 23.0$ minutes.

Table 3.8 provides the optimal fuel quantities obtained for holding depending on five arrival hours, compared with the average amount of standard fuel loaded

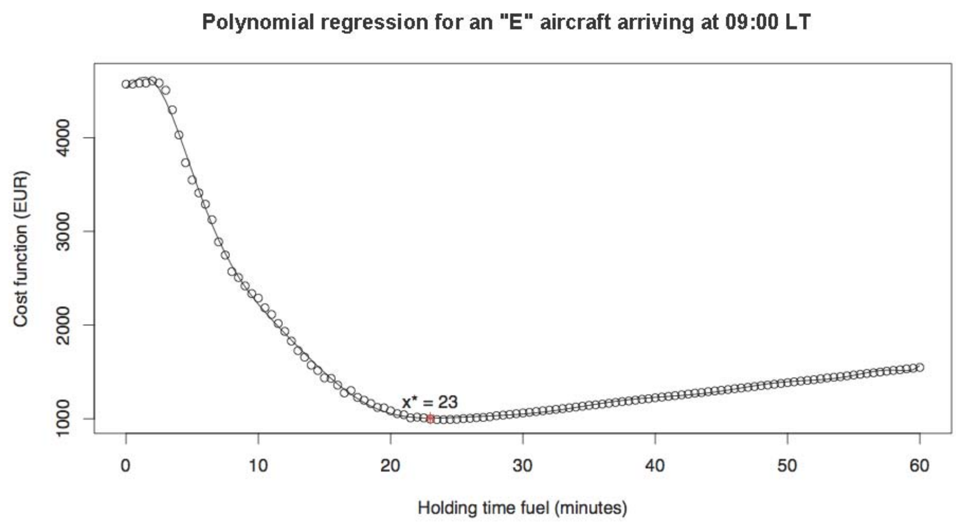


Figure 3.8: Polynomial regression metamodel and optimal fuel.

under similar circumstances, both expressed in minutes. In the last row, we have

Table 3.8: "E" aircraft optimal holding fuel.

Hour (LT)	09:00	14:00	17:00	21:00	23:00
Standard fuel	20	30	20	20	0
Optimal fuel	23 (98.61%)	25 (94.57%)	17 (96.81%)	19 (99.45%)	0

also indicated, in parentheses, the approximate quantile of the holding time distribution that corresponds to such value. Note that at 23:00 LT is customary not to fuel for holding due to a very low air traffic intensity.

We can see that the optimal fuel is only higher than the standard fuel loaded at 09:00 (+3 minutes). At 23:00 the optimal and standard fuel loaded coincide. However, at 14:00 (-5 minutes), 17:00 (-3 minutes) and 21:00 (-1 minutes) the optimal fuel is lower than the standard fuel loaded. With these numbers, the fuel budget for this aircraft type, at this airport, would be reduced in EUR 12,075 per year approximately, where we have estimated the current fuel price as 75 EUR/min.

We have simulated one year of operations under the optimal fuel for holding policy displayed in Table 3.8, in order to estimate the number of diversions that might take place under such new policy. Table 3.9 shows the average number of annual operations that each aircraft type performs at each arrival time. We only consider the 09:00 and 14:00 arrival times for the sake of simplicity, and because these arrival times are representative of the busiest periods at conventional international airports. Besides, for the other arrival times no diversions were registered on

2011, and, therefore, there would be little margin for improvement.

Table 3.9: Number of operations at each arrival time considered.

Hour (LT)	"E" aircraft	"A" aircraft
09:00	115	505
14:00	91	480

For each operation, we generate a holding time y from the corresponding mixture given by the parameters in Table 3.6. Should this time be greater than the corresponding optimal fuel for holding in Table 3.8, the flight would need to be diverted to an alternate airport. Otherwise, the aircraft would just land after holding for y minutes. We have replicated this scheme 10,000 times. We show on the left panel of Figure 3.9 the barplot for the number of diverted flights, together with the actual number of diversions registered in 2011 for the incumbent period of time (represented by a vertical red line).

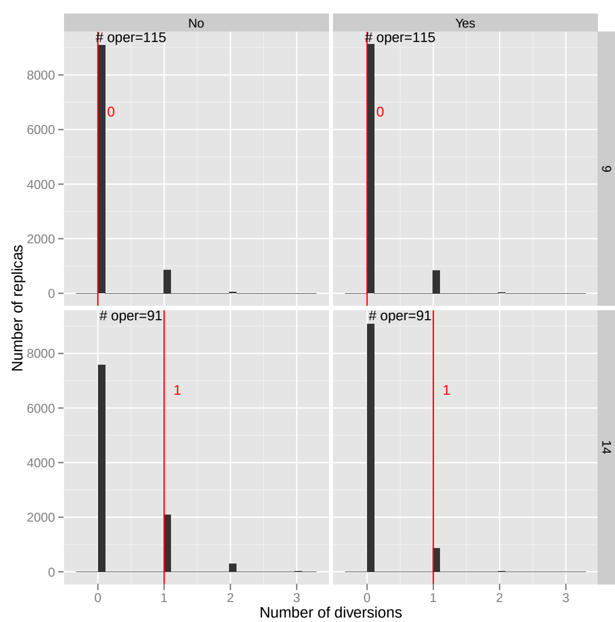


Figure 3.9: Simulation of diverted flights for an "E" aircraft type.

The labels "No" and "Yes" stand for whether or not we have taken into account passenger soft costs, as we discuss below.

For instance, let us consider an "E" aircraft arriving at 14:00 LT, something which occurs 91 times per year. As we can observe, the number of diversions (out of the 91 operations) would be 0 or 1 with probabilities 0.7579 and 0.2092, respectively, whereas the registered data in 2011 was 1 diverted flight. In other words, the probability that, with this new policy, we would face at least one diversion within a normal year is, approximately, 0.2421. Moreover, the expected number of diverted flights within a year under this policy would be 0.2782. These results confirm that the optimal policy we propose is quite reliable, in that it keeps the risk of having to divert under satisfactorily low limits. On the other hand, if we consider the arrival time at 09:00 LT, there would be no margin for improvement, as no diversions, out of 115 operations, were registered in 2011 for the "E" aircraft type. However, with our optimal policy we can still assure that, with probability 0.9089, we will not perform worse than that. Furthermore, the expected number of diverted flights would be, in this case, 0.0961.

Nonetheless, we were still concerned about further reducing these small probabilities of diverting, as we were aware of the negative consequences they produce on airlines, in terms of costs, image, and loss of market share. In this regard, a step forward in our analysis was to consider soft cost passenger delay. For that, we used the structure of costs per average passenger, delay minute and delayed flight suggested by Cook et al. (2012). We, then, repeated the previous optimization to obtain the new optimal quantities of fuel to be loaded, displayed in Table 3.10

Table 3.10: "E" aircraft optimal holding fuel with soft costs.

Hour (LT)	09:00	14:00	17:00	21:00	23:00
Standard fuel	20	30	20	20	0
Optimal fuel	23 (98.61%)	29 (98.17%)	18 (97.59%)	19 (99.45%)	0

Comparing Tables 3.8 and 3.10, we can observe that the difference in minutes appears to be rather small (four and one minute more at 14:00 and 17:00 LT, respectively). However, if we consider all operations within a year for an "E" aircraft at such operation times, the cost balance changes from a benefit of approximately EUR 12,075 to a loss of EUR 15,300 per year, i.e., an overall increase on the costs of EUR 27,375. This amount is practically negligible when compared with the actual fuel budget of major airlines. Moreover, with these new optimal fuel quantities, we simulated again one-year operations, summarizing the results on the right panel of Figure 3.9. As expected, we have further reduced the probability of diverting, especially at 14:00 LT, where the probability of having to divert at least once within a year has reduced now to 0.0912, being the expected number of diverted flights within a year 0.095. On the other hand, the situation for 09:00 LT remains, in practice, the same, as no extra fuel is recommended to be loaded for this arrival time.

Summarizing, we claim that a slightly more cautious policy for fueling for holding, including passengers' soft costs, is advisable, as it does not entail a large increase in the airline's balance account (being, in some cases the balance even favorable), while it reduces the risk of having to divert, a situation with punishing consequences for the companies.

Short-haul flight

We briefly consider now a second case, regarding a narrow-body "A" aircraft type ($\sqrt{MTOW} = 8.69$, $C_{Handling}$ = EUR 1,200) arriving at the incumbent airport after 2 hours and 30 minutes of flight time (t_{std}). In this case, the aircraft was dispatched at the departing airport with 720 kg of fuel for a 20 minute standard holding. We set the arrival time at 09:00 LT. In this case, the minimum of the resulting adjusted metamodel was at $x^* = 25.5$ minutes.

In the first two rows in Table 3.11, we show again the standard fuel for holding loaded depending on the arrival time at five hours, compared with the optimal fuel quantities obtained for holding under similar circumstances. We can observe

Table 3.11: "A" aircraft optimal holding fuel.

Hour (LT)	09:00	14:00	17:00	21:00	23:00
Standard fuel	20	30	20	20	0
Optimal fuel	25 (99.52%)	32 (99.39%)	19 (98.35%)	19 (99.45%)	0
Optimal fuel (with s.c.)	26 (99.73%)	32 (99.39%)	19 (98.35%)	20 (99.79%)	0

than the optimal fuel is higher than the standard fuel loaded at 09:00 ($+5$ minutes) and 14:00 ($+2$ minutes), and slightly lower at 17:00 and 21:00 (-1 minute). These deviations from the standard fuel amount lead to an approximate annual increase of EUR 76,670, which may appear quite high, but we must recall that the number of operations at such times for this type of aircraft is also very high (around 1,800 times per year), compared with those of the "E" aircraft.

We now simulate the one-year scenario, obtaining the results on the left panel of Figure 3.10.

As we can observe, the improvement is significant for 09:00 LT, an arrival time at which 3 "A"-type flights had to be diverted in 2011. With our optimal policy, we assure that, with probability 0.867, no flights will be diverted, being the expected number of diverted flights within a year 0.1407. Our new policy compares also favorably at 14:00 LT, when one flight was diverted in 2011, and now the probability of not having to divert is 0.8514, with an annual expected number of diverted flights of 0.0736.

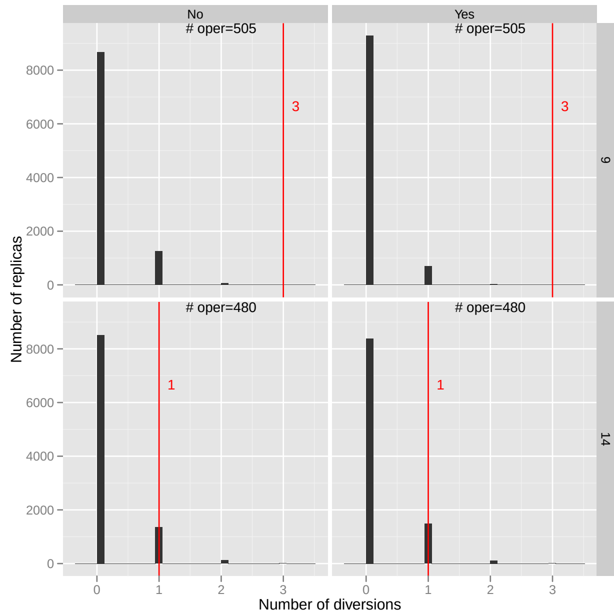


Figure 3.10: Simulation of diverted flights for an “A” aircraft type.

As in Section 3.4.4, we now take into account passengers’ soft costs and repeat the above computations. The new results for optimal fuel quantities for holding are summarized in the last row of Table 3.11. As we can observe, we only increase the fuel for holding by one minute at 09:00 and 21:00 LT with respect to the case in which soft costs are not taken into account, which amounts to an annual extra cost of EUR 11,110.

Finally, we repeat the simulation for one year, displaying the results on the right panel of Figure 3.10. As we can observe, the improvement is significant for 09:00 LT, where the probability of not having to divert is 0.9286, with an expected number of diverted flights of 0.0736 within a year. The results for 14:00 LT have not changed, as we have recommended to load the same amount of fuel for holding than when passengers’ soft costs were not taken into account.

Handling risk aversion

So far we have assumed risk neutrality in costs within the incumbent airline. We shall briefly explore now the impact of risk aversion and proneness in the fueling for holding policy. In the first case, the utility function will be strategically equivalent to $u(c) = -\exp(r \cdot c)$, with $r > 0$, where c are the consequences (costs) associated with the policy. In the second case, the utility function is strategically equivalent to $u(c) = \exp(-r \cdot c)$, again with $r > 0$. For the sake of brevity, we shall consider only the case of the "E" aircraft. We present in Table 3.12 the results for the optimal fuel quantities to be loaded under risk aversion and risk proneness, for the values $r = 10^{-5}$, $5 \cdot 10^{-6}$ and 10^{-6}, comparing them with those results for standard and optimal (under risk neutrality) situations, already shown in Table 3.10 and displayed here again for ease of reading. As we can observe, the results for risk

Table 3.12: "E" aircraft optimal holding fuel with risk aversion.

Hour (LT)	r	09:00	14:00	17:00	21:00	23:00
Standard fuel	—	20	30	20	20	0
Optimal fuel (with s.c.)	—	23	29	18	19	0
Risk aversion	10^{-5}	25.5	33	22	20	0
	$5 \cdot 10^{-6}$	25.5	32	22	20	0
	10^{-6}	24	30.5	21	20	0
Risk proneness	10^{-5}	16.5	14	14.5	16.5	0
	$5 \cdot 10^{-6}$	22	28	17	19	0
	10^{-6}	22.5	28.5	17.5	19	0

aversion reflect the tendency of loading more fuel than that recommended under the risk neutrality optimal policy, aiming at reducing as much as possible the probability of having to divert, without incurring, on the other hand, in prohibitive costs due to this extra fuel loaded. This behavior would be typical of large, traditional, companies whose main goal is to cultivate the loyalty of their customers, and that, by all means, try to avoid their dissatisfaction.

On the contrary, companies which are risk-prone would be, e.g., low cost companies, in which fuel costs are the most limiting share in their budgets. The results displayed in the last three rows of Table 3.12 illustrate this phenomenon, with optimal quantities of fuel to be loaded slightly smaller than those recommended within the risk-neutral policy (an especially aggressive policy is observed for $r = 10^{-5}$). It is clear that such risk-prone policy does not regard the consequences of a possible diversion to an alternate airport as extremely punitive.

3.5 Discussion

Fueling costs are the bulk of the operating costs of airlines. Given the increasing costs of fuel, companies are exploring ways to reduce them. However, unpunctuality due to ATFM delays is increasing as well, due to traffic congestion at airports. This factor is a source of dissatisfaction for many passengers, potentially causing a reduction in market share, specially for business class passengers and those with connecting flights in hub-and-spoke network airlines.

Thus, it seems important to provide models to support decisions about the optimal fuel quantity for holding to be loaded on an airplane, looking for a balance between fuel costs and other operational costs arising as a consequence of diverting to the alternate airport. In this Chapter, we have provided such model based on a continuous decision tree. Key issues within our model are a thorough analysis of the involved cost distributions as well as a detailed forecast model of such delays. We have focused on those costs which are better understood, asking an expert for judgmental elicitation when needed. We have left aside little understood issues such as the "value of passenger time", which has been used in transport services and infrastructure cost-benefit analyses, but are not yet sufficiently studied in the air transport industry. Nor we have considered "CO_2 emission charges" because, to our knowledge, there are not sufficient data available nowadays to tackle this issue.

The issues discussed in this Chapter show the need for integrating the different airline divisions to analyze and assess operational costs such as fueling, delays or airport diversions in a global manner. It is specially important to have decision models related with passenger delay costs, which are difficult and complex to quantify. For this aim, our model takes into account all DOCs involved, and has proved successfully that, by optimizing the fuel loaded for holding, the diversion costs to the alternate airport, due to ATFM delays, can be considerably reduced.

With our case studies, we have considered different scenarios, comparing, among other things, the fuel cost against the probability of having to divert to the alternate airport. For instance, for the wide-body aircraft landing at 14:00 LT, the inclusion of delayed passengers' soft costs led to an increase of 4 minutes in the optimal fuel (EUR 27,300 per year). However, the probability of not having to divert at that time raised from 0.7579 to 0.9088. Given this, the question would be how much the airline's executives would be willing to pay to reduce the chances of having to divert to an alternate airport. However, should we aim at supporting better decisions, we should also analyze the main features of the company's fleets, assessing all the involved costs jointly. Again, we have to keep in mind that our optimal fuel represents a balance between fuel costs and other DOC such as maintenance, handling, and passenger costs. In this sense, it would be particularly important for the airlines to compare the costs derived from an optimal fuel for holding policy with DOC plus the more difficult to understand passengers' soft costs. In our approach we have monetized all costs. Another possibility would be to consider a biattribute utility function, with an attribute in relation with standard costs, and another one in relation with soft costs, and perform sensitivity analysis on the weights of the utility function. With our model, we have simulated situations with low and high soft costs, finding little differences in the fuel needed to be loaded for holding, which, on the other hand, reduce considerably the probability of diversion to the alternate airport, minimizing drastically the likelihood of dissatisfaction among the airline's passengers.

The proposed model could be turned into a decision support system for the fueling for holding problem for any specific aircraft type and airport of the airline network. Clearly, the outputs of the model would depend on the quality and reliability of the available data. Thus, a considerable preliminary effort should be required to analyze the data for all the airports in which a company operates. Note also that such system should be open to intervention, see West and Harrison (1997): a model similar to the one we have used could be employed under normal circumstances; however, in the event of exceptions (bad weather, terrorist events,...) leading to extraordinary delays, we would intervene in the forecasting model and run again the decision model to obtain the appropriate fueling for holding decisions.

Chapter 4

Runway Overrun Excursions at Landing

4.1 Introduction

According to Boeing (2012), around 37% of the accidents involving the worldwide commercial jet aircraft fleet occurred during the final approach and landing flight phases. Although over the last 50 years there has been a significant reduction in the number of accidents, the 10-year moving average of fatal runway-overrun accidents involving global large commercial jets during 1992–2011 shows a worsening trend, see Rosenkrans (2012). Van Es (2005) conducted a study based on landing overrun data drawing several relevant conclusions:

- The African region showed the highest landing overrun accident rate, followed by Central/South America and Asia, with rates higher than one accident per million landings. The rates in other regions were less than half the above mentioned rate, with less than one accident per two million landings. North America had the lowest rate.
- No statistically significant difference was found between the estimated landing overrun accident rate for commercial transport jet and turboprop aircrafts.
- At a global scale, the landing overrun accident rate reduced by a factor of three over the period 1970–2004. This reduction is most likely the result of several factors including improvements in braking devices (antiskid, autobrakes etc.), better understanding of runway friction issues, and safety awareness campaigns.

Runway overruns during landing constitute a top safety focus for regulatory agencies and the entire commercial aviation industry, see Jenkins and Aaron (2012).

Runway excursions must be considered as a major threat to aviation safety, as they account for approximately 25% of all incidents and accidents in air transport, and 96% of all runway accidents. For that reason, several manufacturers of commercial jetliners and avionic systems are implementing a combination of procedural and flight deck enhancements, along with crew education and training, to mitigate runway landing overruns. These solutions improve safety by increasing the crew situational awareness through the in-flight continuous landing distance computation on final approach and ground roll, even under low visibility conditions. These new safety technologies focus on human-factors-driven flight deck design enhancements. However, they need to be practical and cost effective to be accepted by the aviation industry. These tools assist flight crew in determining the required runway length and where on the runway the airplane is expected to stop. According to Jenkins and Aaron (2012), when flight crews are aware and in control of the situation, they will make effective and timely decisions to ensure a safe landing. In the cockpit, decision making is good only for a defined time window due to the dynamics of the situation and, sometimes, decisions are irreversible. Besides, when workload is too high because of bad weather, time pressure, etc., the quality of decision making processes deteriorates and risk may be underestimated, possibly because prior similar situations were successfully managed, see Pelegrin (2010) or Tinsley et al. (2012).

According to Bateman (2009), many of the world's runway lengths were designed for propeller aircraft and were located many years ago, but growth of the surrounding population was not anticipated, nor were the advent of turbo-jet aircrafts and the large increase in air traffic worldwide. In spite of these limitations, regulatory authorities and industry continue to investigate several runway safety solutions, as extended runway overrun areas with restraining ends, runway safety areas, or runway end safety areas, which provide better access for firefighters and rescue teams, or Engineered Material Arresting Systems, which have proved their safety value in several events. Nevertheless, it must be emphasized that today's commercial aviation is operating at such a high level of safety that breakthroughs in its improvement will be hard-won, and will require deeper levels of analysis and increasingly sophisticated tools and methods, see Stolzer et al. (2008).

As in many other industries and scenarios, such as natural disasters, terrorism, nuclear power plant accidents or chemical plant explosions, runway overrun excursion accidents occur with a very low probability, but their implications may be very severe. They are known as "low probability/high consequence" (lp/hc) events. Thus, it is still critical to further reduce their rate of occurrence and, in this sense, extensive efforts and analysis are being devoted to minimize the corresponding occurrence probability. Existing methods and models are useful but, because of the potentially catastrophic consequences of these failures, new modeling perspectives can add new insights to enhance safety, see Luxhøj and Coit (2006). For such purpose, we introduce in this chapter a probabilistic risk model for runway excursions that can help the airline community and aerodrome operators to improve safety as analytical methods may aid to turn their safety-related data into valuable information. Our model also aims at helping in assessing and managing this kind of threats through identifying which airports or runways pose the greatest risk level.

The structure of the chapter is as follows. We first describe in Section 4.2 general issues about runway excursion events. In Section 4.3, we briefly review some definitions regarding landing distance, as this will play a key role in our model. In Section 4.4, we provide our model for runway overrun excursion risk at landing, illustrated in Section 4.5 through a case study. We end up with some discussion.

4.2 Runway overrun excursions at landing

A runway excursion can occur on takeoff or landing. It is defined as an event in which an aircraft departs from the end (overrun) or the side (veer-off) of the runway surface, sometimes with catastrophic consequences. According to the FSF (2009), over the 14-year period from 1995 to 2008, commercial transport aircrafts were involved in a total of 1,429 accidents involving major or substantial damage. Of those, 431 accidents (30%) were runway-related, 417 of which (97%) were runway excursions. In general, the likelihood of fatalities in a runway-related accident is greater in incursion and confusion accidents, while only a small percentage of runway excursion accidents are fatal. However, since the overall number of these events is so high, that small percentage accounts for a large number of fatalities. Over the 14-year period analyzed, 712 people died in runway excursion accidents. In addition, during that period, the takeoff excursion accident rate decreased, but the number of landing excursions showed an increasing trend, see Figure 4.1.

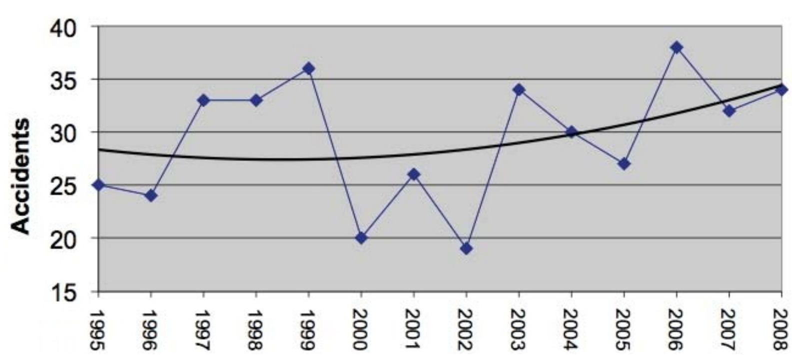


Figure 4.1: Landing excursion trend. Source: FSF (2009).

The Boeing event data from 2003 to 2010 showed the following frequencies of occurrence with respect to factors contributing to landing overruns, see Jenkins and Aaron (2012):

- 68% occurred after stable approaches.
- 55% touched down within the touchdown zone.
- 90% landed on an other-than-dry runway.
- 42% landed with a tailwind of 5 kt or greater.

There are multiple contributing factors to runway overruns, whose causes may begin as early as the approach briefing, or that may occur even once the airplane is on the ground and decelerating, see Figure 4.2.

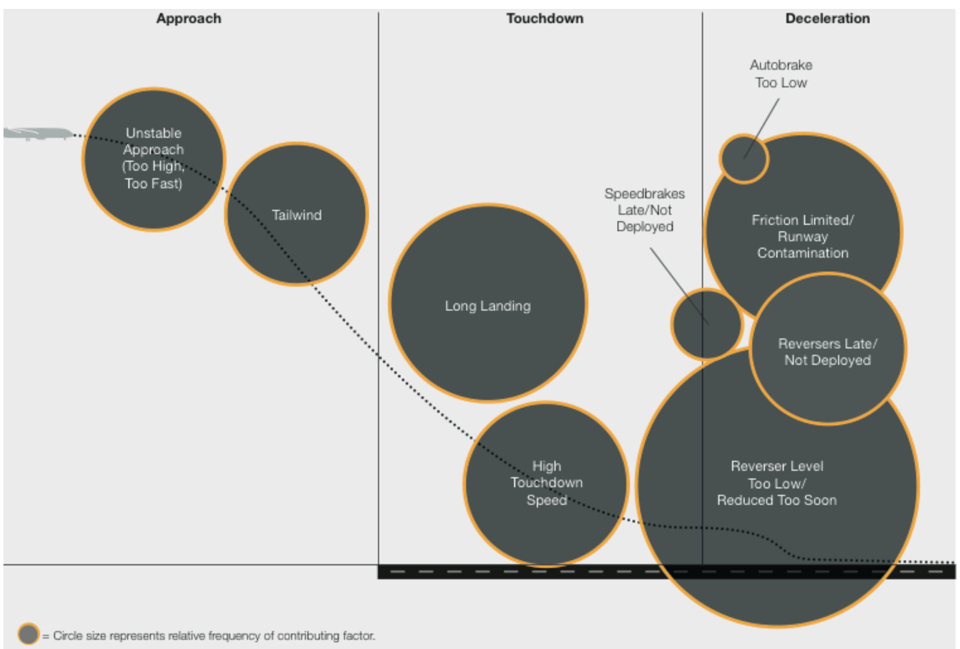


Figure 4.2: Causes of landing overrun excursions. Source: Jenkins and Aaron (2012).

Moreover, because of the fact that the time window for pilot decision making is extremely small, pilots involved could have prevented most of the more serious events under study should they have observed some basic rules as, e.g., crossing the runway threshold at the correct height ($\approx$ 50 ft) and Final Approach Speed (Vapp), landing within the touchdown zone, or promptly and completely using the thrust reversers and other deceleration devices, see Rosenkrans (2012). Mitigating any single factor will not, in general, fix this safety problem and adopting an overall solution including more than one type of countermeasures seems necessary.

Van Es (2005) suggests that there appears to be a significant increase in landing overrun risk when one of the following factors is present while landing:

- Touching down far beyond the threshold (long landing).
- Excessive approach speed.
- Visual approach.
- Significant tailwind present.
- High on approach.
- Wet/flooded runway, and/or snow/ice/slush covered runway.
- Non-precision approach.

Hall et al. (2008) conducted a Functional Hazard Analysis (FHA) to identify the relevant factors associated with aircraft overrun events. They classified them into six different categories, see Figure 4.3. Most cases date from 1982 to 2006.

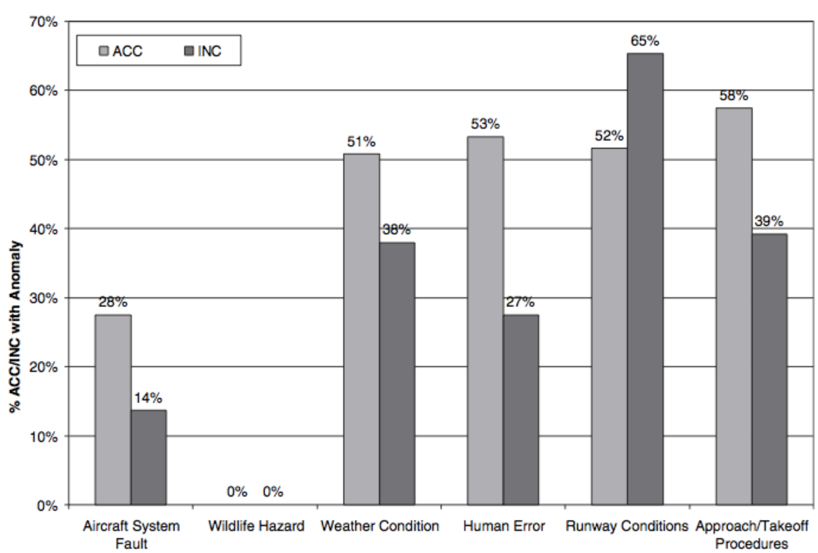


Figure 4.3: Contributing factors for runway excursion events. Source: Hall et al. (2008).

As we can observe, the highest incidence factors for overrun accidents were approach procedures, human error, runway conditions and weather conditions. The same factors appeared also as causes of overrun incidents, although with different relevance. Furthermore, these authors suggest three additional factors with high incidence for landing overruns:

- Long touchdown.
- High speed during approach.
- Presence of rain.

In 2006, the FSF was asked to conduct a study of runway safety, see Burin (2011). After a comprehensive analysis of relevant data, the FSF confirmed that runway excursions pose a greater risk than other types of runway-related accidents. The data showed that one out of every three turbojet airplane accidents and one out of every four turboprop accidents correspond to a runway excursion. As a tool for reducing runway-excursion accidents, the Foundation developed the following "Safe Landing Guidelines" (SLGs):

1. Fly a stabilized approach.
2. Height at threshold crossing should be at most 50 ft.
3. Speed at threshold crossing has to be within V_{REF} and $V_{REF} + 10$ kt of indicated airspeed.
4. Tailwind is no more than 10 kt for non-contaminated runway, no more than 0 kt for a contaminated runway.
5. Touch down on runway centerline at the touchdown point.
6. After touchdown, promptly transition to the desired deceleration setting: brakes, spoilers/speed brakes, and thrust reverses or equivalent (e.g., lift dump).
7. Speed is less than 80 kt with 2,000 ft of runway remaining.

As established by Burin (2011), data have shown that the risk of an approach-and-landing accident increases if any of the guidelines are not met. Even more important, the overall risk of an accident is greatly increased if more than one of the guidelines are not met. Indeed, some combinations of elements may be highly conductive to a runway excursion, such as landing long and fast, or landing with tailwind on a contaminated runway. However, to our knowledge, causal relationships among these variables have not been established yet.

The main FSF guideline is to fly a stabilized approach. Unstable approaches increase the risk of landing runway excursions, as it seems proved that continuing an unstabilized approach is a factor in 40% of all approach-and-landing accidents, see AIRBUS (2006), and in 32% according to a Boeing analysis, see Jenkins and Aaron (2012). An approach is considered stabilized when the following criteria are met before or when reaching 1,000 ft above the airport elevation under Instrument

Meteorological Conditions (IMC), or 500 ft above the airport elevation under Visual Meteorological Conditions (VMC):

- The aircraft is on the correct lateral and vertical flight path.
- Only small changes in heading/pitch required to keep the correct flight path.
- The indicated aircraft speed is not more than V_{REF} + 20 kt and not less than V_{REF} (these figures could be slightly different depending on the aircraft type).
- The aircraft is in the correct landing configuration.
- The sink rate is not greater than 1,000 ft $\cdot$ min^{-1}. If an approach requires a greater sink rate, a special briefing should be conducted.
- Power setting or thrust is stabilized, usually above idle and appropriate for the aircraft configuration, and is not below the minimum power for approach, as defined by the Aircraft Operating Manual.
- All briefings and checklists have been conducted.
- Instrument Landing System (ILS) approaches must be flown within one dot of the glideslope and localizer.

The next FSF guideline is to cross the runway threshold at 50 ft. Closely related with the threshold crossing height is the threshold crossing speed. FSF (2009) shows that touchdown long/fast is much more strongly associated with factors inherent in overruns, whereas touchdown hard/bounce has a relatively weak association. In veer-off excursions, touchdown hard/bounce seems associated with both stabilized and unstabilized approaches, see Table 4.1.

Table 4.1: Risk factor interactions in landing excursion overruns. Source: FSF (2009).

*Number of Events With the Cited Pairs of Factors**	Stabilized Approach (47 events)	Unstabilized Approach (87 events)	Go-Around Not Conducted (107 events)	Touchdown Long/Fast (118 events)	Touchdown Hard/ Bounce (17 events)	Runway Contamination (101 events)	Crosswind (18 events)	Tailwind (30 events)	Gusts/ Turbulence/ Wind Shear (22 events)
Stabilized Approach			13	13	3	25	3	8	6
Unstabilized Approach			84	77	8	43	7	14	13
Go-Around Not Conducted	13	84		91	14	53	10	19	18
Touchdown Long/Fast	13	77	91		15	53	9	20	14
Touchdown Hard/Bounce	3	8	14	15		5	2	7	5
Runway Contamination	25	43	53	53	5		10	15	16
Crosswind	3	7	10	9	2	10		7	16
Tailwind	8	14	19	20	7	15	7		8
Gusts/ Turbulence/ Wind Shear	6	13	18	14	5	16	16	8	

** Cells highlighted in yellow are those where the co-existence of two factors is greater than or equal to 20 percent*

Regarding tailwind, the FSF recommends a maximum acceptable value of 10 kt. Tailwind entails a greater risk when combined with a contaminated runway.

Jenkins and Aaron (2012) showed that for the runway excursion event, 42% of the aircrafts landed with a tailwind of 5 kt or greater, and 90% on an other-than-dry runway. Another relevant issue in minimizing the risk of an excursion is the zone at which the aircraft should touch down. In this regard, the FSF SLGs recommend that the aircraft should be slowed down to less than 80 kt by the time it reaches the point on the runway where only 2000 ft (610 m) of pavement remain.

On the other hand, in order to asses and manage excursion risks we should consider the costs engaged by this safety issue. Honeywell (2009) estimated the economic impact to US airlines and business aviation operators at around USD 900 millions annually. Such costs included:

- Direct costs, such as damage to own or others' property, contractual liabilities or injury to passengers/crew; and
- Indirect costs, such as flight cancellations, repositioning of replacement aircraft and other factors, that may be up to three times higher than direct costs in some cases.

Bateman (2009) calculated runway excursion costs from 2005–2007, averaging about USD 500 million per year, see Table 4.2.

Table 4.2: Runway excursion accidents losses (2005–2007). Source: Bateman (2009).

Date	Location	Aircraft Type(s)	Accident	Fatalities/ Serious	Estimated Loss in USD
9 Nov 2007	Quito, Ecuador	A340	Landed long & tailwind		**200 M**
26 Oct 2007	Butuan, Philippines	A320	Landed long		**60 M**
16 Sep 2007	Phuket, Thailand	MD-82	Landed long & fast		**20 M**
17 Jul 2007	Sao Paulo, Brazil	A320	Landed long	199F + 11S	**602 M**
17 Jul 2007	Santa María, Colombia	EMB-190	Landed long		**37 M**
7 Mar 2007	Yogyakarta, Indonesia	B737-400	Landed long & fast	23F + 15S	**52 M**
25 Dec 2006	Makassar, Indonesia	B737-400	Landed long		**15 M**
17 Nov 2006	Barranquilla, Colombia	DC-10	Floated on wet runway		**20 M**
10 Oct 2006	Stord, Norway	BAe-146	Landed long		**7 M**
3 Oct 2006	Tarakan, Indonesia	B737-200	Landed long		**15 M**
7 Sep 2006	Lagos, Nigeria	B727	Landed long & fast		**10 M**
9 Jul 2006	Irkutsk, Russia	A310	Thrust reverser	131F	**70 M**
4 Jun 2006	Managua, Nicaragua	DC-10	Landed long		**15 M**
4 Mar 2006	Surabaya, Indonesia	MD-82	Thrust reverser		**15 M**
8 Dec 2005	Chicago, IL, USA	B737-700	Late thrust reverser	1F + 1S	**35 M**
2 Aug 2005	Toronto, Canada	A340	Landed long & tailwind	11S	**235 M**
1 Jul 2005	Chittagong, Bangladesh	DC-10	Unstable approach		**25 M**
24 Jan 2005	Dusseldorf, Germany	B747-200	Landed long & fast		**60 M**
8 Jan 2005	Cali, Colombia	MD-83	Landed long & fast		**25 M**
				354 Fatal **38 Serious**	**USD 1,518 M** **USD 506 M/year**

Mitigation measurements that could reduce runway excursion risk need to be cost-effective to be accepted by the aviation industry. Technology funding for an airport to improve runway infrastructure is often constrained by difficult economic and political conditions. Moreover, the implementation of safety technologies for an aircraft is further constrained by the severe economic conditions faced by most aircraft operators, see Bateman (2009).

To sum up, taking into account all these previous studies and together with expert judgement techniques, we have designed a mind map to visualize the relevant factors associated with runway overrun excursion events, see Buzan and Buzan (2006). Figure 4.4 will aid us in devising our model.

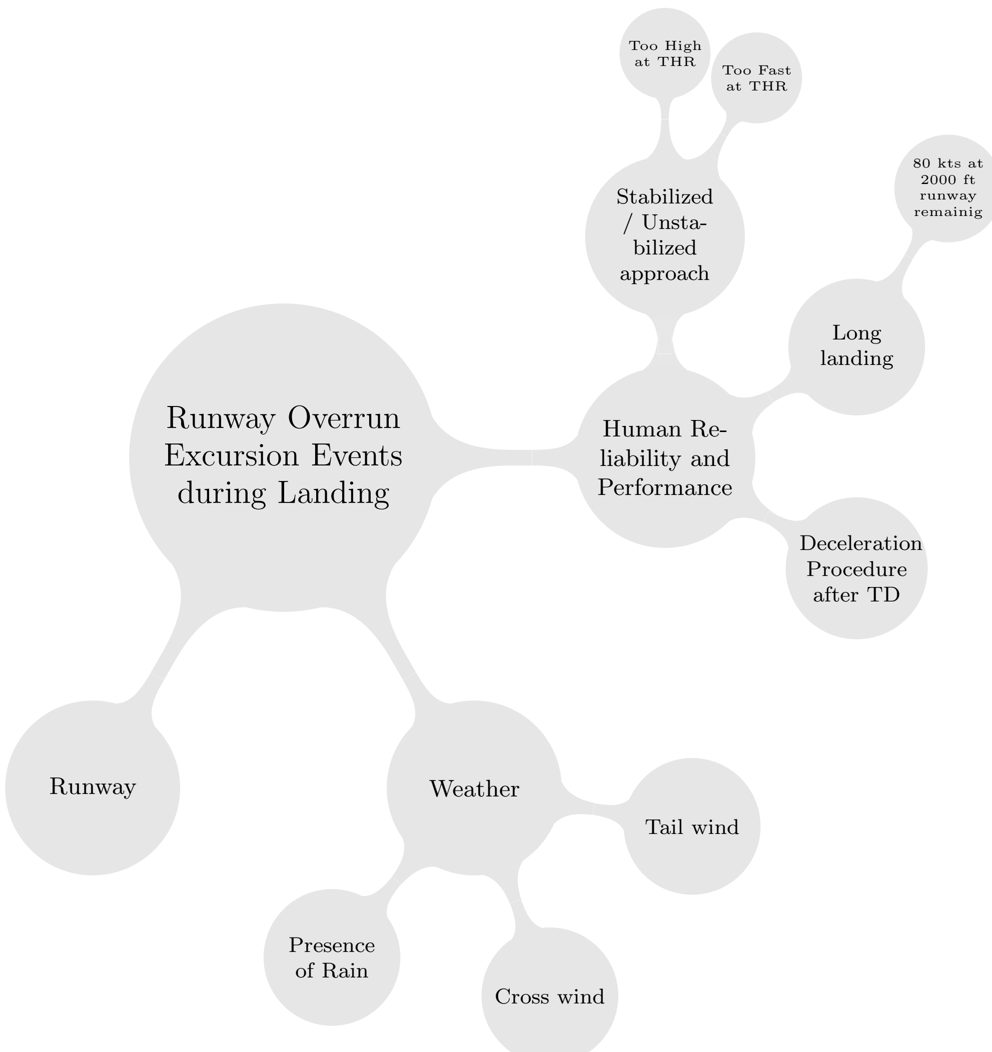


Figure 4.4: Mind map of factors associated with runway excursions.

Weather and human reliability and performance would appear to be the main contributing factors for runway excursion events at landing. In reference to weather, two factors with high incidence are rain and wind (specifically, the cross and tailwind components). Of course, weather conditions might be more influential at some specific airports. Moreover, the available landing distance of the runway may also influence the landing pilot performance, see Cheng et al. (2007). For this reason, we have also included the runway as a factor in our mind map. Different circumstances are often cited when discussing rushed and unstabilized approaches, long landings or deceleration procedures after touchdown (reverse thrust or autobrake procedures), but most of them are related with human reliability and performance (fatigue, pressure due to flight schedule, lack of awareness of tailwind component, incorrect anticipation of aircraft deceleration characteristics, etc.). Regarding flying an unstabilized approach, excess of height and approach speed when overflying the threshold seems to motivate a significant increase of landing overrun risk. Finally, we have included a branch referring to long landing to highlight that this factor will reduce the remaining runway available to decelerate the aircraft to 80 kt. This last concept will have a significant role in our model.

4.3 Landing distance performance

As we have discussed in previous sections, there is no single factor dominating day-to-day landing operations. Aircraft landing field performance may be influenced by many variables frequently interrelated. According to Cheng et al. (2007), some interesting findings are:

- The airborne distance is strongly influenced by the threshold crossing height.
- Lighting conditions do not affect airborne distance.
- The ground roll distance is strongly affected by the available landing distance.
- The autobrake setting has a significant influence on the ground roll distance.
- Runway conditions do not have a measurable influence on the ground roll distance. Indeed, in general, the reduced braking action on a slippery runway is counteracted by the use of a higher autobrake setting.
- The available runway length has a strong influence on the overall behavior of pilots during landing.

Along with the various circumstances which can affect landing distance, see Section 4.2, we should acknowledge that the assessment of the available landing distance margins at the time of arrival is complicated due to many factors, see Kornstaedt and Lignee (2010), including:

- The multitude of methods and formats for assessing and reporting the runway surface condition.
- The lack of explicit regulations regarding the in-flight landing distance assessment.
- The variety of landing performance data formats published by manufacturers or operators for in-flight use.

Since the remaining runway distance at landing will have a key role in our model, we briefly review some of the main definitions used in relation with such concept.

- *Actual Landing Distance (ALD)*. This is the distance demonstrated during airplane certification measured between a point 50 ft above the runway threshold and the point where the aircraft comes to a complete stop, see Figure 4.5.

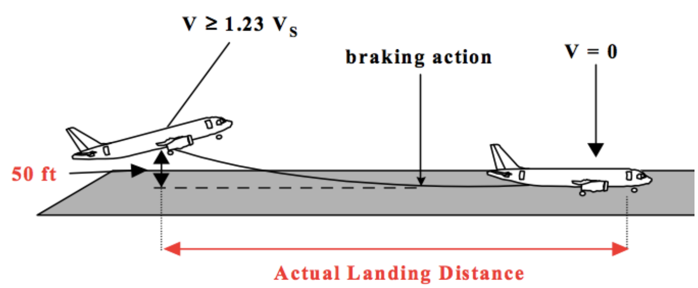


Figure 4.5: Actual landing distance (ALD). Source: AIRBUS (2002).

  To determine the ALD, several conditions must be met: airplane in landing configuration, stabilized approach, etc., see AIRBUS (2002) or EU (2008). ALDs are published at sea level, given a reference temperature and in the absence of wind. Corrections for pressure altitude, longitudinal wind, reverse thrust, planned approach speed, automatic landing and autobrake are typically provided, but not for runway slope or temperature. A downslope runway or one with higher than reference temperature will typically make the achievable landing distance longer than the published one, see Kornstaedt and Lignee (2010).

- *Landing Distance Available (LDA)*. The length of the runway which is declared available by the appropriate authority and suitable for the ground run of an airplane landing, see EU (2008).
- *Required Landing Distance (RLD)*. Distance derived by applying a factor to the ALD which is used for dispatch purposes; i.e., for selecting the destination

and alternate airports. The RLD for dispatch must be shorter than the declared LDA for the intended runway.

- *Landing Distance (LD)*. This is the total distance taken by an airplane from over the threshold at screen height to land and come to a complete stop. The total landing distance begins when the aircraft overflies the threshold at a theoretical height of 50 ft. Until that moment, if an ILS is available, the airplane should follow a straight approach path with a standard 3° Glide Slope (GS). The ICAO standards specify that the GS will cross the runway threshold at a height between 50 and 60 ft. Assuming a normal GS antenna location, the GS intercepts the runway surface at about 1000 ft (≈ 300 m) from the threshold. At a height h_f above the runway, the airplane begins the flare, which is the transition from the straight approach path to the horizontal ground roll. The flight path for the flare can be considered a circular arc with radius R, see Anderson (1999). During the flare, the pilot aims at reducing the vertical component of the velocity, the Rate of Descent (R/D). Aircrafts are not designed to touch down routinely at the R/D that exits along the glide path. Thus, a flare maneuver must be executed to reduce the descent rate to less than 3 ft $\cdot$ s^{-1} (≈ 1 m $\cdot$ s^{-1}) at touchdown (TD), the point at which the main wheels touch the runway, see Kayton and Fried (1997). A landing is considered successful if the mainwheel touchdown occurs along the so-called Touch Down Zone (TDZ) between 150 m and 900 m from the runway threshold. In theory, aircrafts touch down at approximately 2000 ft from the threshold with a speed reduction during the flare of around 5% to 10%. After the main-gear touchdown, air distance, the aircraft lowers its nose wheel and performs the ground roll. During this final phase, the aircraft is brought to rest through the deceleration devices: the spoilers to reduce the wing lift, the reverse thrust from the engines and the wheel brakes.

4.4 A model for runway overrun excursion risk at landing

We provide now a model to assess the risk of overrun at a given runway, under various conditions. Our aim here is to provide a comparison of several runways or airports in terms of the probability of excursion at landing, as a way to show potentially more dangerous infrastructures. This may point out operators or safety agencies towards runways in which special care needs to be taken into account under certain operational conditions. Our model will relate overrun probabilities with potentially triggering factors, therefore suggesting the introduction of mitigation measures. We focus here on the probability of runway excursions, without paying attention to the entailed consequences. Thus, we implicitly assume that we shall be comparing homogenous runways, in the sense of having all of them a similar operational environment.

We have built a probabilistic influence diagram for runway overrun, see Nielsen and Jensen (2007) and Cowell et al. (2007). For this, we have used the information available in Section 4.2 and our mind map, which summarizes the information available from manufacturers, operators and safety agencies, some of the results presented in Cheng et al. (2007), expert judgement and data analyzed with the aid of the GeNIe (2013) modeling environment, which uses Bayesian search learning as the building algorithm, see Riggelsen (2008). Our final probabilistic influence diagram, see Figure 4.6, expresses what we believe are the main variables and factors involved in the runway excursion phenomenon and their relations. The thickness of an arc is automatically adjusted by GeNIe to represent the strength of influence between two directly connected nodes.

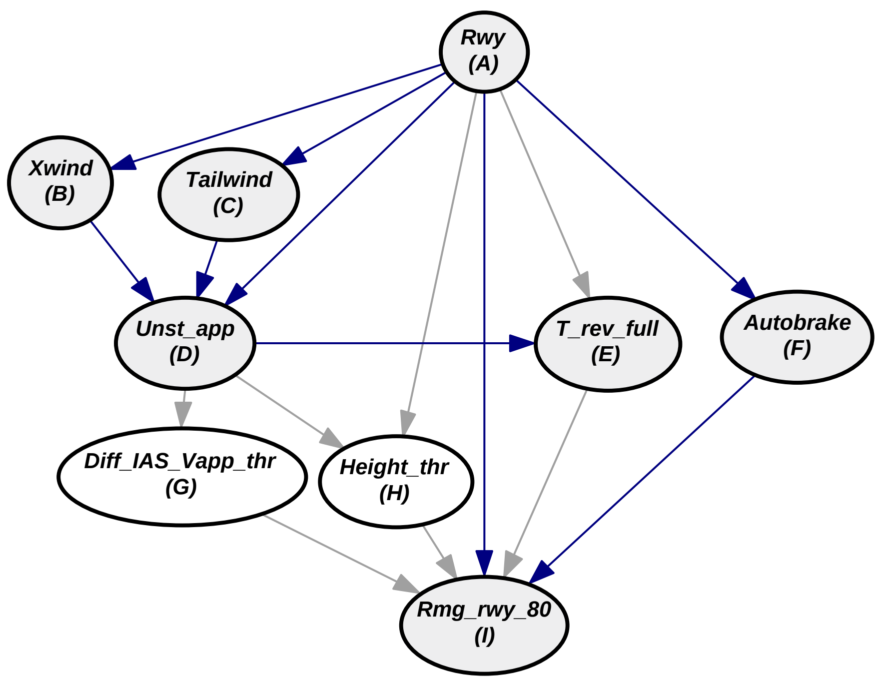


Figure 4.6: Probabilistic influence diagram of factors related with overrun events.

As a key variable, we have chosen the remaining runway at 80 kt (I), measured in ft. According to the FSF SLGs, see Section 4.2, the risk of an accident increases greatly if the aircraft is not slowed down to less than 80 kt by the time it reaches the point on the runway where only 2000 ft (610 m) of LDA remain. The other eight variables included in the model, from left to right and top to bottom, are:

(A) Runway. A categorical variable which identifies the relevant runway.

(B) Crosswind component. It is the crosswind at threshold measured in knots (kt). It is a nonnegative continuous variable discretized to the nearest integer by the onboard avionics system.

(C) Tailwind component. It indicates the tailwind at threshold measured in knots (kt), with the same features as (B).

(D) Stabilized/unstabilized approach. It is a categorical variable with two possible values: stabilized or unstabilized approach.

(E) Maximum reverse thrust. It is a continuous nonnegative variable measured in seconds (s), describing the time that the maximum reverse thrust is operated during ground roll.

(F) Autobrake. A categorical variable with three possible values at landing: no autobrake, low and medium. At each landing, just one value can be selected.

(G) Difference between the Indicated AirSpeed (IAS) and the Final Approach Speed (Vapp) at threshold which is measured in knots (kt). IAS is the airspeed read directly from the airspeed indicator and Vapp represents the lowest selectable speed plus wind corrections. Therefore, it may be negative (IAS $<$ Vapp) or positive (IAS $>$ Vapp).

(H) Height at threshold. It is a continuous nonnegative variable measured in feet (ft). When its value is 0 ft, the aircraft touches down at the threshold.

To build the graph, we used an initial version based on our experience and information collected, and feed in the Bayesian search algorithm to obtain our solution, which we checked for soundness. We found all (appearing and missing) links relevant, except for the possible connection between crosswind and tailwind, which did not appear relevant based on the used data. We decided to leave it as it is, and check for possible correlations in specific cases.

As a consequence, the proposed influence diagram defines a probabilistic model through

$$p(a,b,c,d,e,f,g,h,i) = \\ p(a)p(b|a)p(c|a)p(d|a,b,c)p(e|a,d)p(f|a)p(g|d)p(h|a,d)p(i|a,e,f,g,h), \quad (4.1)$$

where we have used p to generically designate a distribution, whether the corresponding variable is continuous or discrete.

We discuss now some uses of such model. As we have mentioned, the critical event to be considered is $I < 2000$. For a given organization, say an airliner, an airport operator or an aviation safety agency, we could compute

$$\Pr(I < 2000),$$

and use it to assess its risk of runway excursions. The higher this probability is, we get a clearer indicator of the riskiness of the analyzed runway or organization. We could use it to rank airliners or airports according to such risk. For a given organization which operates at several runways, we could compute the risk of runway excursion at each of them through

$$\Pr(I < 2000 | A = \underline{a}).$$

This could help us in ranking runways according to such probabilities.

These calculations may be performed through standard probabilistic computations. Indeed, we have

$$\begin{aligned}
\Pr(I < 2000) &= \int_{-\infty}^{2000} p(i)\,\mathrm{d}i = \\
&= \int_{-\infty}^{2000} \left[\int \cdots \int p(i|a,e,f,g,h) p(a) p(e|a,d) p(f|a) p(g|d) p(h|a,d) \times \right. \\
&\qquad \left. \times\ p(d|a,b,c) p(b|a) p(c|a)\,\mathrm{d}c \cdots \mathrm{d}a \right] \mathrm{d}i.
\end{aligned}$$

However, the integral above will not be typically manageable. We can approximate its value through Monte Carlo simulation with

$$\Pr(I < 2000) \approx \frac{\{\# : 1 \leq k \leq N :\ i_k < 2000\}}{N},$$

for $\{i_k\}_{k=1}^{N} \sim p(i)$. Since we do not have $p(i)$ to sample from directly, we may set up a composition sampler as follows:

Algorithm 1: Sampling from I

```
For k = 1 to N
    Repeat
        Sample a_k ~ p(a)
        Sample b_k ~ p(b|a_k),  c_k ~ p(c|a_k),  f_k ~ p(f|a_k)
        Sample d_k ~ p(d|a_k, b_k, c_k)
        Sample e_k ~ p(e|a_k, d_k),  g_k ~ p(g|d_k),  h_k ~ p(h|a_k, d_k)
        Sample i_k ~ p(i|a_k, e_k, f_k, g_k, h_k)
        k = k + 1
```

Now, using Bayes' formula, we can express

$$\Pr(I < 2000|A = \underline{a}) = \frac{\Pr(I < 2000, A = \underline{a})}{\Pr(A = \underline{a})}.$$

$\Pr(I < 2000, A = \underline{a})$ is obtained in a similar manner, through

$$\begin{aligned}\Pr(I < 2000, A = \underline{a}) &= \int_{-\infty}^{2000} p(i, \underline{a})\, \mathrm{d}i = \\ = \Pr(A = \underline{a}) \int_{-\infty}^{2000} \Bigg[\int \cdots \int & p(i|\underline{a}, e, f, g, h) p(e|\underline{a}, d) p(f|\underline{a}) p(g|d) p(h|\underline{a}, d) \times \\ & \times\ p(d|\underline{a}, b, c) p(b|\underline{a}) p(c|\underline{a})\, \mathrm{d}c \cdots \mathrm{d}e \Bigg] \mathrm{d}i.\end{aligned}$$

We, therefore, get that $\Pr(I < 2000|A = \underline{a}) = \int_{-\infty}^{2000} [\int \cdots \int p(i|\underline{a}, e, f, g, h) p(e|\underline{a}, d)$ $p(f|\underline{a}) p(g|d) p(h|\underline{a}, d) p(d|\underline{a}, b, c) p(b|\underline{a}) p(c|\underline{a})\, \mathrm{d}c \cdots \mathrm{d}e]\, \mathrm{d}i$, and we can approximate its value through Monte Carlo simulation

$$\frac{\{\# : 1 \leq k \leq N :\ i_k < 2000\}}{N},$$

where $\{i_k\}_{k=1}^{N}$ is a sample from Algorithm 2.

Algorithm 2: Sampling from $I|A = \underline{a}$

```
For k = 1 to N
    Repeat
        Sample b_k ~ p(b|a), c_k ~ p(c|a), f_k ~ p(f|a)
        Sample d_k ~ p(d|a, b_k, c_k)
        Sample e_k ~ p(e|a, d_k), g_k ~ p(g|d_k), h_k ~ p(h|a, d_k)
        Sample i_k ~ p(i|a, e_k, f_k, g_k, h_k)
        k = k + 1
```

We may be also interested in computing such probabilities under given conditions. For example, we could assess the probability under severe wind conditions, say

$$\Pr(I < 2000|A = \underline{a}, B > \underline{b}, C > \underline{c}),$$

for certain cutoff wind speeds $\underline{b}, \underline{c}$. This may help us in setting alarms to crew by letting them know an eventual increase in overrun risk given the current or foreseen wind conditions. Using Bayes' formula, we can express

$$\Pr(I < 2000|A = \underline{a}, B > \underline{b}, C > \underline{c}) = \frac{\Pr(I < 2000, A = \underline{a}, B > \underline{b}, C > \underline{c})}{\Pr(A = \underline{a}, B > \underline{b}, C > \underline{c})}.$$

Then, Pr$(I < 2000, A = \underline{a}, B > \underline{b}, C > \underline{c})$ is obtained in a similar manner as before, through

$$\begin{aligned}\Pr(I < 2000, A = \underline{a}, B > \underline{b}, C > \underline{c}) &= \int_{-\infty}^{2000} \int_{\underline{c}}^{\infty} \int_{\underline{b}}^{\infty} p(i, \underline{a}, b, c)\, \mathrm{d}b\, \mathrm{d}c\, \mathrm{d}i = \\ = \Pr(A = \underline{a}) \int_{-\infty}^{2000} \int_{\underline{c}}^{\infty} \int_{\underline{b}}^{\infty} \Big[\int \cdots \int & p(i|\underline{a}, e, f, g, h) p(e|\underline{a}, d) p(f|\underline{a}) p(g|d) \times \\ & \times\ p(h|\underline{a}, d) p(d|\underline{a}, b, c) p(b|\underline{a}) p(c|\underline{a})\, \mathrm{d}c \cdots \mathrm{d}e \Big]\, \mathrm{d}b\, \mathrm{d}c\, \mathrm{d}i.\end{aligned}$$

The probability in the denominator is

$$\Pr(A = \underline{a}, B > \underline{b}, C > \underline{c}) = \Pr(A = \underline{a}) \cdot \Pr(B > \underline{b}|\underline{a}) \cdot \Pr(C > \underline{c}|\underline{a}).$$

After canceling the common term Pr$(A = \underline{a})$, the rest of the numerator is approximated by

$$\frac{\{\# : 1 \leq k \leq N :\ i_k < 2000,\ b_k > \underline{b},\ c_k > \underline{c}\}}{N},$$

based on the same sampler outlined in Algorithm 2, using the output $\{i_k, b_k, c_k\}_{k=1}^{N}$. The rest of the denominator would be obtained from the initial assessments.

Another interesting quantity would be

$$\frac{\Pr(I < 2000|A = \underline{a}, D = \text{unstabilized})}{\Pr(I < 2000|A = \underline{a}, D = \text{stabilized})},$$

which has the form of a likelihood ratio. When this quantity is much bigger than 1, this suggests a much more dangerous condition under an unstabilized approach, possibly hinting at the implementation of additional mitigation measures to improve situational awareness in a given runway. Using Bayes' formula, we can express

$$\Pr(I < 2000|A = \underline{a}, D = \underline{d}) = \frac{\Pr(I < 2000, A = \underline{a}, D = \underline{d})}{\Pr(A = \underline{a}, D = \underline{d})}.$$

The probability on the numerator is obtained through

$$\begin{aligned}\Pr(I < 2000, A = \underline{a}, D = \underline{d}) &= \int_{-\infty}^{2000} p(i, \underline{a}, \underline{d})\, \mathrm{d}i = \\ = \Pr(A = \underline{a}) \int_{-\infty}^{2000} \Big[\int \cdots \int & p(i|\underline{a}, e, f, g, h) p(e|\underline{a}, \underline{d}) p(f|\underline{a}) p(g|\underline{d}) \times \\ & \times\ p(h|\underline{a}, \underline{d}) p(b|\underline{a}) p(c|\underline{a})\, \mathrm{d}c \cdots \mathrm{d}e \Big]\, \mathrm{d}i.\end{aligned}$$

The probability in the denominator is

$$\Pr(A = \underline{a}, D = \underline{d}) = \Pr(A = \underline{a})\Pr(D = \underline{d}|A = \underline{a}).$$

We cancel out the common terms, and the remaining of the numerator is approximated by simulation through

$$\frac{\{\# : 1 \leq k \leq N : \; i_k < 2000\}}{N},$$

where $\{i_k\}_{k=1}^N$ is obtained from Algorithm 3.

Algorithm 3

```
For k = 1 to N
    Repeat
        Sample e_k ~ p(e|a,d),  f_k ~ p(f|a),  g_k ~ p(g|d),
          h_k ~ p(h|a,d)
        Sample i_k ~ p(i|a,e_k,f_k,g_k,h_k)
        k = k + 1
```

The rest of the denominator is approximated by Monte Carlo as follows:

$$\begin{aligned} \Pr(D = \underline{d}|A = \underline{a}) &= \iint p(b|\underline{a})p(c|\underline{a})\Pr(D = \underline{d}|\underline{a}, b, c)\, \mathrm{d}b\, \mathrm{d}c \\ &\approx \frac{1}{N}\sum_{k=1}^{N} \Pr(D = \underline{d}|\underline{a}, b_k, c_k), \end{aligned}$$

for a sample $\{b_k, c_k\}_{k=1}^N$ from $\{p(b|\underline{a})p(c|\underline{a})\}$.

We may be also interested in assessing the risk of runway excursion when not using the reverse at full thrust, or operating the reverse thrust at idle, during the ground roll,

$$\Pr(I < 2000|A = \underline{a}, E \leq \underline{e}),$$

for certain cutoff maximum reverse thrust time $\underline{\mathrm{e}}$. This issue is relevant since by using the reverse thrust at full, together with other deceleration devices as the autobrake, the aircraft would reduce the landing roll. Using Bayes' formula, we can express

$$\Pr(I < 2000|A = \underline{a}, E \leq \underline{e}) = \frac{\Pr(I < 2000, A = \underline{a}, E \leq \underline{e})}{\Pr(A = \underline{a}, E \leq \underline{e})}.$$

The probability on the numerator is obtained through

$$\Pr(I < 2000, A = \underline{a}, E \leq \underline{e}) = \int_{-\infty}^{2000} \int_{-\infty}^{\underline{e}} p(i, \underline{a}, e)\,\mathrm{d}e\,\mathrm{d}i =$$

$$= \Pr(A = \underline{a}) \int_{-\infty}^{2000} \int_{-\infty}^{\underline{e}} \Big[\int \cdots \int p(i|\underline{a}, e, f, g, h) p(e|\underline{a}, d) p(f|\underline{a}) p(g|d) p(h|\underline{a}, d) \times$$

$$\times\ p(d|\underline{a}, b, c) p(b|\underline{a}) p(c|\underline{a})\,\mathrm{d}c \cdots \mathrm{d}f \Big]\,\mathrm{d}e\,\mathrm{d}i,$$

which is approximated by

$$\Pr(I < 2000, A = \underline{a}, E \leq \underline{e}) \approx \Pr(A = \underline{a}) \frac{\{\# : 1 \leq k \leq N :\ i_k < 2000,\ e_k \leq \underline{e}\}}{N}.$$

This can be estimated using the same sampler outlined in Algorithm 2, using the output $\{i_k, e_k\}_{k=1}^{N}$. The probability in the denominator is obtained as follows

$$\Pr(A = \underline{a}, E \leq \underline{e}) = \int_{-\infty}^{\underline{e}} \iiint p(\underline{a}, b, c, d, \underline{e})\,\mathrm{d}b\,\mathrm{d}c\,\mathrm{d}d\,\mathrm{d}e$$

$$= \int_{-\infty}^{\underline{e}} \iiint \Pr(A = \underline{a}) p(b|\underline{a}) p(c|\underline{a}) p(d|\underline{a}, b, c) p(e|\underline{a}, d)\,\mathrm{d}b\,\mathrm{d}c\,\mathrm{d}d\,\mathrm{d}e$$

$$= \Pr(A = \underline{a}) \int_{-\infty}^{\underline{e}} \iiint p(b|\underline{a}) p(c|\underline{a}) p(d|\underline{a}, b, c) p(e|\underline{a}, d)\,\mathrm{d}b\,\mathrm{d}c\,\mathrm{d}d\,\mathrm{d}e$$

$$\approx \Pr(A = \underline{a}) \frac{\{\# : 1 \leq k \leq N :\ e_k < \underline{e}\}}{N},$$

where $\{b_k, c_k, d_k, e_k\}_{k=1}^{N}$ is a sample from $\{p(b|\underline{a}) p(c|\underline{a}) p(d|\underline{a}, b, c) p(e|\underline{a}, d)\}$. As before, we cancel out the $\Pr(A = \underline{a})$ terms.

Finally, we could also be interested on the risk regarding different autobrake settings for a specific runway, such as

$$\frac{\Pr(I < 2000|A = \underline{a}, F = \text{Low})}{\Pr(I < 2000|A = \underline{a}, F = \text{None})},$$

or

$$\frac{\Pr(I < 2000|A = \underline{a}, F = \text{Medium})}{\Pr(I < 2000|A = \underline{a}, F = \text{None})}.$$

which, again, may be viewed as likelihood ratios. When these quantities are much bigger than 1, this would suggest much more dangerous conditions under a nonoperating autobrake system, possibly hinting at the use of autobrake at such runway. Using Bayes' formula, we can express

$$\Pr(I < 2000|A = \underline{a}, F = \underline{f}) = \frac{\Pr(I < 2000, A = \underline{a}, F = \underline{f})}{\Pr(A = \underline{a}, F = \underline{f})}.$$

The probability on the numerator is

$$\begin{aligned}\Pr(I < 2000, A = \underline{a}, F = \underline{f}) &= \int_{-\infty}^{2000} p(i, \underline{a}, \underline{f})\,\mathrm{d}i = \\ = \Pr(A = \underline{a}) \int_{-\infty}^{2000} \bigg[\int \cdots \int &p(i|\underline{a}, e, \underline{f}, g, h) p(e|\underline{a}, d) p(g|d) p(h|\underline{a}, d) \times \\ &\times\; p(d|\underline{a}, b, c) p(b|\underline{a}) p(c|\underline{a})\,\mathrm{d}c \cdots \mathrm{d}e \bigg]\,\mathrm{d}i.\end{aligned}$$

We can approximate its value through Monte Carlo simulation

$$\Pr(I < 2000, A = \underline{a}, F = \underline{f}) \approx \Pr(A = \underline{a}) \frac{\{\# : 1 \leq k \leq N :\; i_k < 2000\}}{N},$$

with $\{i_k\}_{k=1}^{N}$ a sample from Algorithm 4.

Algorithm 4

```
For k = 1 to N
    Repeat
        Sample b_k ~ p(b|a),  c_k ~ p(c|a)
        Sample d_k ~ p(d|a, b_k, c_k)
        Sample e_k ~ p(e|a, d_k),  g_k ~ p(g|d_k),  h_k ~ p(h|a, d_k)
        Sample i_k ~ p(i|a, e_k, f, g_k, h_k)
        k = k + 1
```

The other probabilities involved

$$\Pr(A = \underline{a}, F = \underline{f}) = \Pr(A = \underline{a}) \cdot \Pr(F = \underline{f}|\underline{a}),$$

are obtained directly from the initial assessment, with $\Pr(A = \underline{a})$ canceled out.

4.5 A case study

We describe now a case study which may be used as a model for related scenarios. We have selected three runways with LDA smaller than 7200 ft (≈ 2200 m), and with similar operational settings, regarding environmental conditions around the airports, see Figure 4.7. Thus, should an incident or an accident happen, it would affect the aircraft and/or passengers and crew.

(a) Runway 01 end (b) Runway 02 end (c) Runway 03 end

Figure 4.7: Runway for the case study. Source: Google Earth.

We have used data from 266 operations over a period of 10 months, all of them referring to the same airline and aircraft type. As a first step, we have investigated possible relationships between cross and tailwind components in the incumbent runways. Figure 4.8 provides scatter plots for both variables, with (upper strip) and without (lower strip) zero tailwind values.

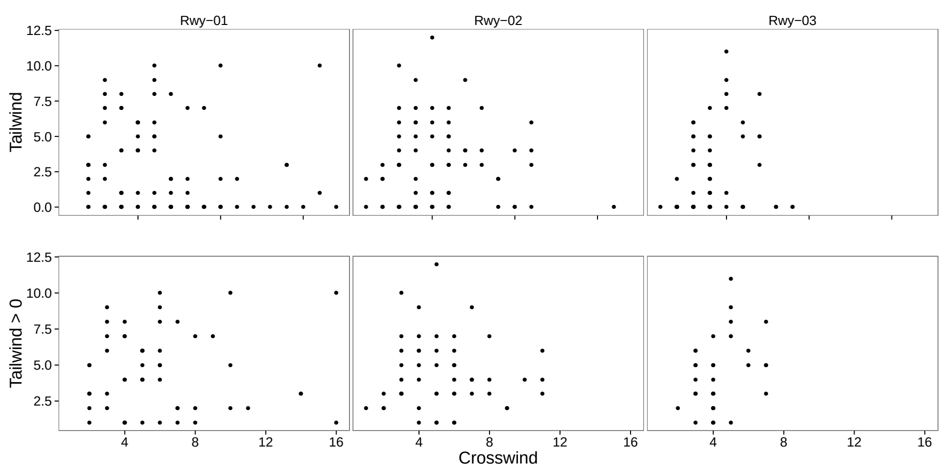


Figure 4.8: Tailwind *vs* crosswind.

The correlation coefficients with zero tailwind values for each runway are, respectively, $r_1 = -0.125$, $r_2 = 0.043$ and $r_3 = 0.213$. None of them suggests strong correlation. As mentioned, we have removed the zero tailwind values, and calculated the correlation coefficients obtaining, respectively, $r_1 = 0.036$, $r_2 = -0.013$ and $r_3 = 0.347$. Again, none of them suggests strong correlation. Therefore, we proceed with our graphical model (4.1), in which crosswind and tailwind are not linked.

We describe now the distributions built at the nodes and, then, illustrate some of the proposed uses of the global model. Given the data available, we shall use the corresponding predictive distribution, possibly based on a sample. For simplicity, we shall eliminate dependence on data at each node, e.g. rather than $p(A|data)$ we shall write $p(A)$.

4.5.1 Modeling runway usage $p(A)$

This is a discrete distribution with values $A = \{1, 2, 3\}$, the runways used. We use a multinomial-Dirichlet model for such purpose. Let (p_1, p_2, p_3) be the proportion of usage of those runways. We have

$$
\begin{aligned}
(p_1, p_2, p_3) &\sim \mathcal{D}ir(1, 1, 1), \\
(x_1, x_2, x_3) &\sim \mathcal{M}(n; p_1, p_2, p_3), \\
p_1, p_2, p_3|data &\sim \mathcal{D}ir(1 + x_1, 1 + x_2, 1 + x_3),
\end{aligned}
$$

where x_1, x_2, x_3 are the number of operations in each runway, shown in Table 4.3.

Table 4.3: Number of operations per landing runway.

Rwy-01	Rwy-02	Rwy-03
104	80	82

When needed, we shall use as estimates the predictive means

$$\Pr(A = j|data) = \frac{1 + x_j}{3 + n}.$$

In this case, we have $\Pr(A = 1|data) = 0.39$, $\Pr(A = 2|data) = 0.30$ and $\Pr(A = 3|data) = 0.31$. This suggests a similar landing probability for all the runways.

4.5.2 Modeling crosswind, given runway $p(B|A)$

All 266 flights entailed nonzero crosswind. We do not differentiate between left and right crosswind components. Figure 4.9 presents the histogram for the crosswind component data at threshold.

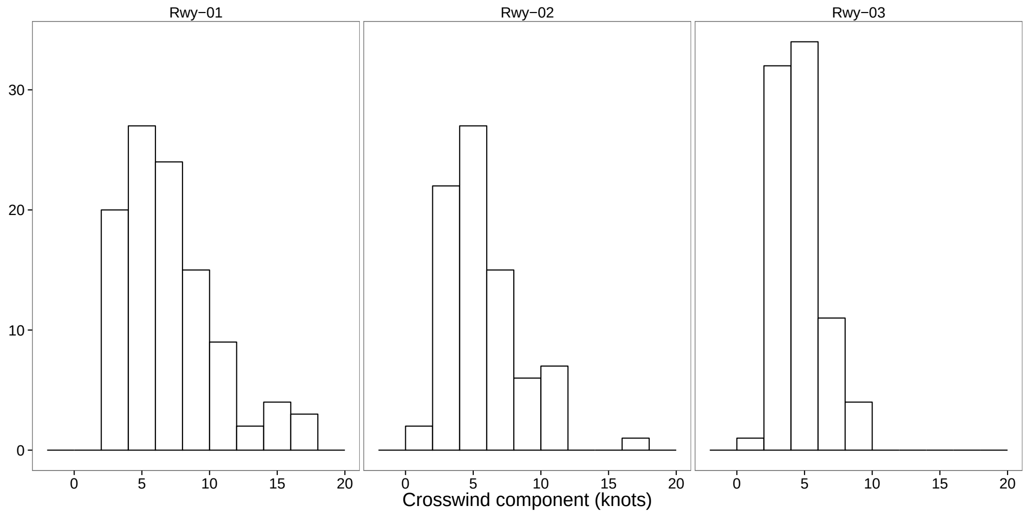


Figure 4.9: Crosswind component at threshold factored by runway.

For each runway, we use an exponential model with a vague gamma prior, see French and Ríos Insua (2000),

$$B|A = j \sim \mathcal{E}xp(\theta_j^b),$$
$$\theta_j^b \sim \mathcal{G}(0.01, 0.01),$$

for runway $j = 1, 2, 3$. A posteriori,

$$\theta_j^b|data \sim \mathcal{G}\left(\alpha_j^b = 0.01 + n_j, \beta_j^b = 0.01 + \sum_{k=1}^{n_j} b_{jk}\right),$$

where n_j is the number of operations at runway j and $b_{jk} \sim B|A = j$ is the k-th crosswind value recorded for runway j. The posteriors for each runway are shown in Table 4.4.

Table 4.4: Posterior summaries of parameters for $B|A$.

	Rwy-01	Rwy-02	Rwy-03
$\theta_j^b\|data$	$\mathcal{G}(104.01, 675.01)$	$\mathcal{G}(80.01, 417.01)$	$\mathcal{G}(82.01, 330.01)$

From the above posteriors, we easily deduce the required predictive densities at the node. For each runway j

$$p(b|A = j, data) = \int p(b|\theta_j^b)p(\theta_j^b|data)d\theta_j^b = \frac{\alpha_j^b(\beta_j^b)^{\alpha_j^b}}{(\beta_j^b + b)^{\alpha_j^b+1}}.$$

4.5.3 Modeling tailwind, given runway $p(C|A)$

Out of 266 flights, 125 entailed no tailwind. Table 4.5 summarizes these data, factored by landing runway.

Table 4.5: Presence of tailwind by landing runway.

Tailwind	Rwy-01	Rwy-02	Rwy-03
No	49	29	47
Yes	55	51	35
Total	104	80	82

Figure 4.10 represents the histogram for the positive tailwind cases. The tailwind operational limit as regulated by the incumbent agency is indicated with a vertical dashed line.

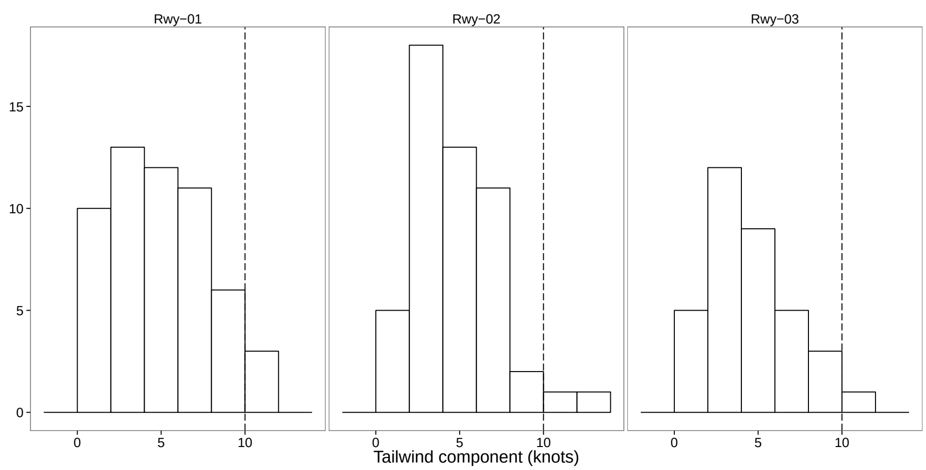


Figure 4.10: Positive tailwind component factored by runway.

We have, then, decomposed the tailwind distribution (C) through the mixture

$$C_j = p_{0j} I_0 + p_{1j} C_j^+,$$
$$p_{0j} + p_{1j} = 1,$$
$$p_{0j}, p_{1j} \geq 0,$$

for each runway, $j = 1, 2, 3$. The first component, I_0, describes the zero tailwind cases; the second one, C_j^+, the positive ones. Based on a noninformative beta-binomial model, see French and Ríos Insua (2000), we get that, a posteriori,

$$p_{1j} | data \sim \mathcal{B}e(1 + x_j, 1 + n_j - x_j),$$

where n_j is the total number of operations in runway j and x_j is the number of operations with nonzero tailwind. We use as an estimate for p_{1j} its posterior mean

$$\frac{1+x_j}{2+n_j}.$$

We model now the nonzero tailwind component through an exponential-gamma model with a vague prior:

$$C_j^+ \sim \mathcal{E}xp(\theta_j^c),$$
$$\theta_j^c \sim \mathcal{G}(0.01, 0.01).$$

A posteriori,

$$\theta_j^c|data \sim \mathcal{G}\left(\alpha_j^c = 0.01 + x_j, \beta_j^c = 0.01 + \sum_{k=1}^{x_j} c_{jk}\right),$$

where $c_{jk} \sim C_k^+$ is the k-th (positive) tailwind value recorded for runway j. The posteriors are shown in Table 4.6.

Table 4.6: Posterior summaries of parameters for $C|A$.

	Rwy-01	Rwy-02	Rwy-03
$p_{1j}\|data$	$\mathcal{B}e(56, 50)$	$\mathcal{B}e(52, 30)$	$\mathcal{B}e(36, 48)$
$\theta_j^c\|data$	$\mathcal{G}(55.01, 247.01)$	$\mathcal{G}(51.01, 221.01)$	$\mathcal{G}(35.01, 148.01)$

At the node, we shall use the following predictive density for each runway j

$$p(c|A = j, data) = \frac{1+n_j-x_j}{2+n_j} I_0 + \frac{1+x_j}{2+n_j} \frac{\alpha_j^c(\beta_j^c)^{\alpha_j^c}}{(\beta_j^c + c)^{\alpha_j^c+1}}.$$

4.5.4 Modeling stability, given runway, cross and tailwind $p(D|A, B, C)$

In our model, the type of approach is influenced by the runway and the wind (cross and tailwind components). We have labeled $d_k = 1$ if the approach is unstabilized and $d_k = 0$, otherwise. We model the probability $p_{jk} = \Pr(d_{jk} = 1|A = j, B, C)$ given the cross and tailwind components at threshold for each runway j. For that purpose, we use logistic regression models

$$\text{logit}(p_{jk}) = \log\left(\frac{p_{jk}}{1-p_{jk}}\right) = \alpha_j^d + B_{jk}\beta_{1j}^d + C_{jk}\beta_{2j}^d,$$

where b_{jk} and c_{jk} are the k-th values of the cross and tailwind components at threshold when landing at runway j.

We assume vague normal priors $\mathcal{N}(0, 10^5)$ for all model parameters. Posterior summaries of the parameters using WinBUGS are given in Table 4.7.

Table 4.7: Posterior summaries of parameters for $p(D|A, B, C)$.

	Rwy-01		Rwy-02		Rwy-03	
	mean	sd	mean	sd	mean	sd
$\alpha^d \vert data$	-12.29	4.21	-7.07	3.11	-7.19	2.34
$\beta_1^d \vert data$	0.59	0.26	0.37	0.29	0.63	0.34
$\beta_2^d \vert data$	0.42	0.28	-8.13	6.13	0.11	0.22

As we can observe, the posterior estimates of β_1^d and β_2^d are slightly positive in all runways, except for β_{22}^d in Rwy-02, which has a large negative value. Note that in this case the posterior variance is quite large, so the estimated value might not be very representative. The same may be said of β_{23}^d for Rwy-03, even if it is positive. According to the results, crosswind has a greater influence than tailwind, except at Rwy-02, where landing under severe tailwind conditions can be particularly delicate. In general, landing under tailwind conditions should, in principle, increase the probability of an unstabilized approach. However, and according to expert opinion, landing at these runways under such windy conditions could increase the situational awareness, and crews would follow the Standard Operating Procedures (SOP) strictly, reducing the probability of an unstabilized approach.

As it is not possible to obtain a closed form expression for the predictive distribution of $p(d|a, b, c, data)$, we use the following sampling scheme for each runway, to obtain a sample from the predictive distribution.

Algorithm 5: Sampling from $p(d|a, b, c, data)$

For $\mathtt{k} = 1$ to $\mathtt{N}$
- Sample $\mathtt{a_k} \sim \mathtt{p(a|data)}$
- Sample $\mathtt{b_k} \sim \mathtt{p(b|a_k, data)}, \mathtt{c_k} \sim \mathtt{p(c|a_k, data)}$
- Sample $\alpha_{\mathtt{k}}^{\mathtt{d}} \sim \mathtt{p}(\alpha_{\mathtt{k}}^{\mathtt{d}}|\mathtt{a_k}, \mathtt{data})$, $\beta_{\mathtt{1k}}^{\mathtt{d}} \sim \mathtt{p}(\beta_1^{\mathtt{d}}|\mathtt{a_k}, \mathtt{data})$, $\beta_{\mathtt{2k}}^{\mathtt{d}} \sim \mathtt{p}(\beta_2^{\mathtt{d}}|\mathtt{a_k}, \mathtt{data})$
- Compute $\mathtt{logit(p_k)} = \alpha_{\mathtt{k}}^{\mathtt{d}} + \mathtt{b_k} \cdot \beta_{\mathtt{1k}}^{\mathtt{d}} + \mathtt{c_k} \cdot \beta_{\mathtt{2k}}^{\mathtt{d}}$
- Sample $\mathtt{u} \sim \mathtt{U}(0, 1)$
- if $\mathtt{u} < \mathtt{p_k}$ then
  - $\mathtt{d_k} = 1$ (unstabilized approach)
- else
  - $\mathtt{d_k} = 0$ (stabilized approach)

4.5.5 Modeling maximum reverse thrust, given runway and stability of approach $p(E|A,D)$

Out of 266 operations, 118 entailed reverse at idle thrust. The remaining 148 landings were with maximum reverse thrust during ground roll. Table 4.8 summarizes these data factored by landing runway and stability of approach.

Table 4.8: Reverse thrust usage during ground roll factored by runway and stability.

Reverse thrust	Stabilized			Unstabilized		
	Rwy-01	Rwy-02	Rwy-03	Rwy-01	Rwy-02	Rwy-03
Idle	39	41	37	0	0	0
Maximum	63	38	42	2	1	3
Total	102	79	79	2	1	3

Note that for Rwy-01, the shortest one, there are more cases with maximum reverse thrust at landing than at Rwy-02 and Rwy-03.

Figure 4.11 represents the maximum reverse thrust in seconds during ground roll factored by landing runways and the stabilization approach requirement. Idle reverse thrust is not represented.

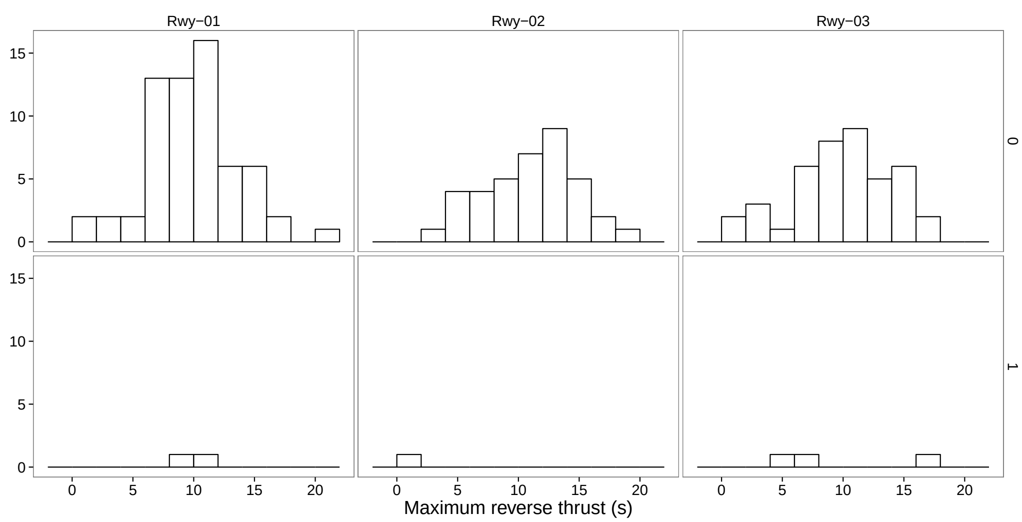


Figure 4.11: Maximum reverse thrust during ground roll factored by approach and runway.

We distinguish the cases for stabilized and unstabilized approaches:

- For a stabilized approach, we decompose the reverse thrust (E) through the mixture

$$E_j = p_{0j} I_0 + p_{1j} E_j^+,$$
$$p_{0j} + p_{1j} = 1,$$
$$p_{0j}, p_{1j} \geq 0,$$

for each runway, $j = 1, 2, 3$. The first component, I_0, describes the idle reverse thrust cases. The second one, E_j^+, the maximum reverse thrust ones. As in Section 4.5.3, and based on a noninformative beta-binomial model, we get that, a posteriori,

$$p_{1j}|data \sim \mathcal{B}e(1 + y_j, 1 + n_j - y_j),$$

where n_j and y_j are, respectively, the number of stabilized operations and the number of such operations with maximum reverse thrust at runway j. We model the maximum reverse thrust duration through an exponential-gamma model with vague prior

$$E_j^+ \sim \mathcal{E}xp(\theta_j^{e,stab}),$$
$$\theta_j^{e,stab} \sim \mathcal{G}(0.01, 0.01).$$

A posteriori,

$$\theta_j^{e,stab}|data \sim \mathcal{G}\left(\alpha_j^e = 0.01 + y_j, \beta_j^e = 0.01 + \sum_{k=1}^{y_j} e_{jk}^{stab}\right),$$

where $e_{jk}^{stab} \sim E_j^+$ is the k-th maximum reverse thrust value recorded under stabilized approach for runway j. The posteriors for each runway j are shown in Table 4.9.

Table 4.9: Posterior summaries of parameters for $E|A, D =$ Stabilized.

	Rwy-01	Rwy-02	Rwy-03
$p_{1j}\|data$	$\mathcal{B}e(64, 40)$	$\mathcal{B}e(39, 42)$	$\mathcal{B}e(43, 38)$
$\theta_j^{e,stab}\|data$	$\mathcal{G}(63.01, 596.01)$	$\mathcal{G}(38.01, 389.01)$	$\mathcal{G}(42.01, 396.01)$

The predictive density for the j-th runway is approximated by

$$p(e|a_j, d = 0, data) = \frac{1 + n_j - y_j}{2 + n_j} I_0 + \frac{1 + y_j}{2 + n_j} \frac{\alpha_j^e (\beta_j^e)^{\alpha_j^e}}{(\beta_j^e + e)^{\alpha_j^e + 1}}.$$

- For an unstabilized approach, there are no zero values in this case, see Figure 4.11, so we model the maximum reverse thrust through an exponential-gamma model, using as a prior distribution the posterior distribution obtained for the nonzero cases in the stabilized approach, i.e.

$$E|A = j, D = 1 \sim \mathcal{E}xp(\theta_j^{e,unst}),$$
$$\theta_j^{e,unst} \sim \theta_j^{e,stab}|data.$$

where $j = 1, 2, 3$ represents the runway. A posteriori,

$$\theta_j^{e,unst}|data \sim \mathcal{G}\left(\tilde{\alpha}_j^e = \alpha_j^e + z_j, \tilde{\beta}_j^e = \beta_j^e + \sum_{k=1}^{z_j} e_{jk}^{unst}\right),$$

where α_j^e and β_j^e are the posterior parameters for $\theta_j^{e,stab}|data$ as shown in Table 4.9, z_j is the number of unstabilized operations with maximum reverse thrust for runway j, and $e_{jk}^{unst} \sim E|A = j, D = 1$ is the corresponding k-th value. The posteriors for each specific runway j are shown in Table 4.10.

Table 4.10: Posterior summaries of parameters for $E|A, D =$ Unstabilized.

	Rwy-01	Rwy-02	Rwy-03
$\theta_j^{e,unst}|data$	$\mathcal{G}(65.01, 615.01)$	$\mathcal{G}(39.01, 389.51)$	$\mathcal{G}(45.01, 422.01)$

From the above posterior, we deduce the required predictive densities

$$p(e|a, d = 1, data) = \frac{\tilde{\alpha}_j^e \left(\tilde{\beta}_j^e\right)^{\tilde{\alpha}_j^e}}{\left(\tilde{\beta}_j^e + e\right)^{\tilde{\alpha}_j^e + 1}}.$$

4.5.6 Modeling autobrake, given runway $p(F|A)$

We use a multinomial-Dirichlet model for each runway. If we use the coding 1-No, 2-Low and 3-Medium, we have

$$(p_1^j, p_2^j, p_3^j) \sim \mathcal{D}ir(1, 1, 1),$$
$$(x_1^j, x_2^j, x_3^j) \sim \mathcal{M}(n_j; p_1^j, p_2^j, p_3^j),$$

where (p_1^j, p_2^j, p_3^j) represent the proportion of usage of the different autobrake system configurations in runway j, and (x_1^j, x_2^j, x_3^j) is the actual number of operations under such configuration. Then, a posteriori,

$$(p_1^j, p_2^j, p_3^j)|data \sim \mathcal{D}ir(1 + x_1^j, 1 + x_2^j, 1 + x_3^j).$$

When needed, we shall use the predictive estimates

$$\Pr(F = \ell | A = j, data) = \frac{1 + x_\ell^j}{3 + n_j}.$$

Table 4.11 shows the values of the estimates and, in parentheses, the available data.

Table 4.11: Posterior estimates and data for autobrake factored by runway.

Autobrake	Rwy-01	Rwy-02	Rwy-03
No (1)	0.21 (22)	0.38 (31)	0.51 (42)
Low (2)	0.12 (12)	0.28 (22)	0.27 (22)
Medium (3)	0.67 (70)	0.34 (27)	0.22 (18)
Total	104	80	82

Note that the autobrake system is mostly used at the shortest runway in which, moreover, the setting at "Medium" is more frequently selected, as it provides the highest deceleration.

4.5.7 Modeling difference between IAS and Vapp, given stability of approach $p(G|D)$

Figure 4.12 represents the variable G, i.e. the difference between IAS and Vapp at threshold, factored by the stabilization approach (D). At threshold, IAS should be equal to Vapp. We have indicated this value with a vertical dashed line.

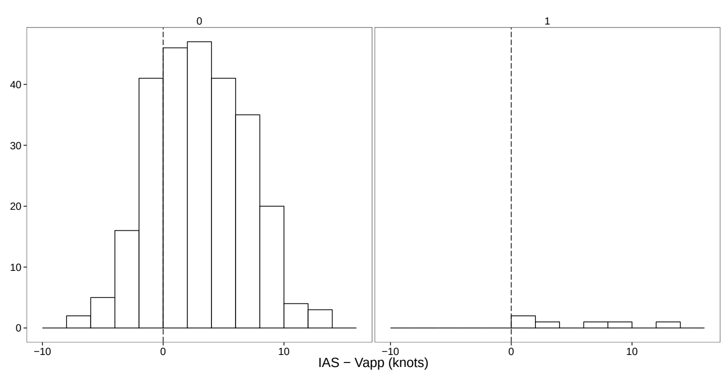


Figure 4.12: Difference between IAS and Vapp factored by approach .

In both cases, stabilized and unstabilized, we assume that G_k follows a normal model

$$G_k | D \sim \mathcal{N}(\mu, \sigma^2).$$

For our analysis, we shall use the standard noninformative prior

$$p(\mu, \sigma^2) \propto \frac{1}{\sigma^2},$$

which yields the posterior

$$p(\mu, \sigma^2 | data) \propto \sigma^{-n-2} \exp\left(-\frac{1}{2\sigma^2} \left[(n-1)s^2 + n(\mu - \bar{g})^2 \right] \right),$$

where s^2 is the sample variance and $\bar{g}$ is the sample mean. We can see that

$$p(\mu | data) \propto \left(1 + \frac{n(\mu - \bar{g})^2}{(n-1)s^2} \right)^{-n/2},$$

which corresponds to a t-distribution with $(n-1)$ degrees of freedom, mean $\bar{g}$ and scale parameter s^2/n, see Gelman et al. (2009). We can finally show that the predictive distribution

$$p(g | d = \ell, data)$$

is a t-distribution with $(n_\ell - 1)$ degrees of freedom, location $\bar{g}_\ell$ and scale parameter $\left(1 + \frac{1}{n_\ell}\right) s_\ell^2$, where n_ℓ is the number of observations, $\bar{g}_\ell$ is the sample average IAS, s_ℓ^2 is the sample variance IAS, being $\ell = \{0, 1\}$ the label for stabilized and unstabilized approach, respectively. Table 4.12 summarizes the relevant parameters.

Table 4.12: Sample size, mean and variance.

	Stabilized	Unstabilized
n	260	6
$\bar{g}$	2.47	5
s^2	14.97	20.80

4.5.8 Modeling height at threshold, given runway and stability of approach $p(H|A, D)$

Figure 4.13 represents the height when aircrafts overfly the threshold (H), factored by landing runway and the stabilization approach requirement. In theory, the aircraft should overfly the threshold at 50 ft, and we have indicated this value with a vertical dashed line.

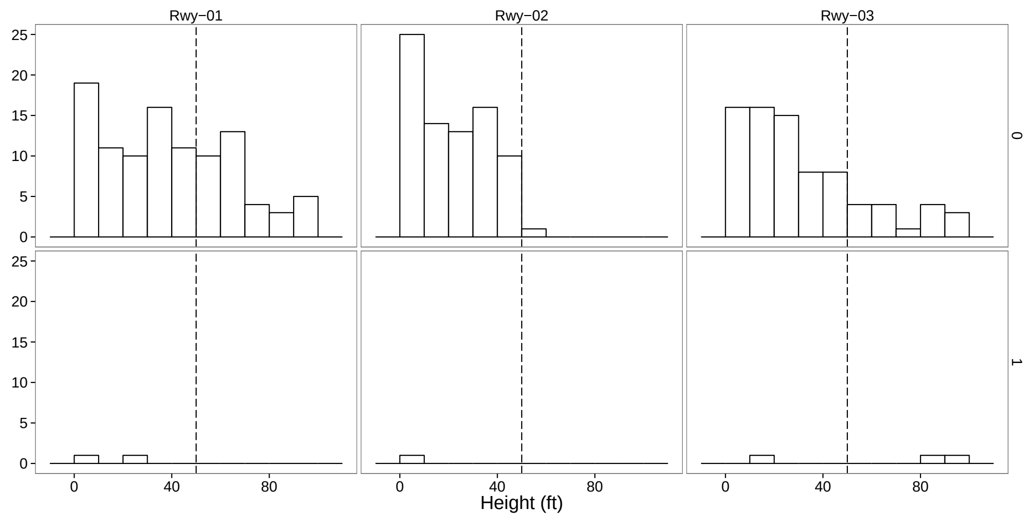


Figure 4.13: Height at threshold factored by approach and runway.

We can model the required predictive density as follows.

- For a stabilized approach, as suggested in Figure 4.13, we consider that, for each runway, the data come from a mixture of, at most, three Weibull distributions: one component for values close to zero, and at most two more components for intermediate to extreme values, although some of these latter components might have a negligible probability. We then assume the mixture model
$$h|a, d = 0 \sim \sum_{m=1}^{3} w_m \, \mathcal{W}e\big(\lambda_m^{h,stab}, \theta_m^{h,stab}\big).$$
We assume a uniform prior for the mixture weights
$$(w_1, w_2, w_3) \sim \mathcal{D}ir(1, 1, 1),$$
and vague priors for the parameters of the Weibull components
$$\lambda_m^{h,stab} \sim \mathcal{G}(0.01, 0.01),$$
$$\theta_m^{h,stab} \sim \mathcal{G}(0.01, 0.01).$$
As it is not possible to obtain a closed expression for the posterior distribution of the parameters $\big(\lambda_m^{h,stab}, \theta_m^{h,stab}\big)$, we have used WinBUGS to that purpose. We detected three components for the first runway and two components for the two other runways, as the third component got a negligible probability. The posterior estimates of the parameters of the components and mixture

weights are summarized in Table 4.13. We have included, in parenthesis, the corresponding standard deviation.

Table 4.13: Posterior parameters for the Weibull mixture (stab. approach).

Rwy	Comp 1			Comp 2			Comp 3		
	$\hat{\lambda}_1^{h,stab}$	$\hat{\theta}_1^{h,stab}$	$\hat{w}_1$	$\hat{\lambda}_2^{h,stab}$	$\hat{\theta}_2^{h,stab}$	$\hat{w}_2$	$\hat{\lambda}_3^{h,stab}$	$\hat{\theta}_3^{h,stab}$	$\hat{w}_3$
1	1.83(0.11)	12.84(0.91)	0.29(0.036)	5.04(0.41)	38.63(2.63)	0.37(0.027)	4.86(0.35)	74.03(3.45)	0.34(0.019)
2	0.88(0.052)	18.46(1.09)	0.48(0.035)	4.78(0.25)	42.18(2.26)	0.52(0.031)	—	—	—
3	0.78(0.051)	24.57(2.25)	0.90(0.047)	5.53(0.31)	82.44(5.60)	0.10(0.0096)	—	—	—

As it is not possible to obtain a closed form expression for the predictive distribution of $p(h|a, d = 0, data)$, we use the following sampling scheme for each runway, to obtain a sample from the required distributions (we drop superscripts $(h, stab)$ for simplicity):

Algorithm 6: Sampling from $p(h|a, d = 0, data)$

For $\mathtt{k} = 1$ to $\mathtt{N}$
- Sample $(\mathtt{w}_1^{\mathtt{k}}, \mathtt{w}_2^{\mathtt{k}}, \mathtt{w}_3^{\mathtt{k}}) \sim \mathtt{w}_1, \mathtt{w}_2, \mathtt{w}_3|\mathtt{data}$
- Sample $\mathtt{m}_{\mathtt{k}} \sim \mathtt{Mult}(1; \mathtt{w}_1^{\mathtt{k}}, \mathtt{w}_2^{\mathtt{k}}, \mathtt{w}_3^{\mathtt{k}})$
- Sample $\lambda_{\mathtt{k}} \sim \lambda_{\mathtt{m}_{\mathtt{k}}}|\mathtt{data}$ and $\theta_{\mathtt{k}} \sim \theta_{\mathtt{m}_{\mathtt{k}}}|\mathtt{data}$.
- Sample $\mathtt{h}_{\mathtt{k}}|\mathtt{a}, \mathtt{d} = 0, \mathtt{data} \sim \mathtt{We}\big(\lambda_{\mathtt{k}}, \theta_{\mathtt{k}}\big)$.
- $\mathtt{k} = \mathtt{k} + 1$

This provides us with a sample $\{h_k\}_{k=1}^N$ from $p(h|a, d = 0, data)$.

- For unstabilized approaches, we only consider two terms in the mixture

$$h|a, d = 1 \sim \sum_{m=1}^{2} \omega_m \, \mathcal{W}e\big(\lambda_m^{h,unst}, \theta_m^{h,unst}\big).$$

In this case, due to the small sample size, we shall not use noninformative priors but, rather, we use the posteriors of the parameters in the stabilized case, and their corresponding weights. For convenience, in Rwy-01 we shall only consider the first two components of the stabilized case. The posterior estimates of the model parameters are summarized in Table 4.14.

Table 4.14: Posterior parameters for the Weibull mixture (unst. approach).

Rwy	Comp 1			Comp 2		
	$\hat{\lambda}_1^{h,unst}$	$\hat{\theta}_1^{h,unst}$	$\hat{\omega}_1$	$\hat{\lambda}_2^{h,unst}$	$\hat{\theta}_2^{h,unst}$	$\hat{\omega}_2$
1	1.79(0.14)	13.01(1.05)	0.41(0.093)	4.88(0.60)	37.89(2.21)	0.59(0.031)
2	0.92(0.049)	18.22(1.01)	0.49(0.031)	4.81(0.24)	42.05(2.17)	0.51(0.036)
3	0.81(0.058)	24.99(2.36)	0.88(0.041)	5.59(0.34)	84.04(5.93)	0.12(0.011)

To estimate the predictive $p(h|a, d = 1, data)$, we will proceed through a similar sampling scheme as in Algorithm 6.

4.5.9 Modeling remaining runway at 80 kt, given runway, reverse thrust, autobrake, IAS and height at threshold $p(I|A, E, F, G, H)$

We have used a linear regression model for the remaining runway distance when the aircraft is decelerated to 80 kt,

$$i_{jk} = \alpha_j^i + E_{jk}\beta_{1j}^i + F_{jk}^{low}\beta_{2j}^{low} + F_{jk}^{med}\beta_{2j}^{med} + G_{jk}\beta_{3j} + H_{jk}\beta_{4j} + \epsilon,$$

where e_{jk}, g_{jk} and h_{jk} are, respectively, the k-th values of the maximum reverse thrust, the difference between the Indicated AirSpeed and Vapp, and the height at threshold, when landing at runway j. On the other hand, f_{jk}^{low} and f_{jk}^{med} are two covariates introduced because of the categorical nature of the Autobrake variable F. We define their values as follows: $f_{jk}^{low} = 1$ if the autobrake is set to "Low", and zero otherwise. Similarly, $f_{jk}^{med} = 1$ if the autobrake is set to "Medium", and zero otherwise. Finally, ϵ is the error term, which is assumed to be normally distributed around zero with variance σ_ϵ^2. We assume a flat prior for the variance $\sigma_\epsilon^2 \sim \mathcal{IG}(0.001, 0.001)$.

We assume vague normal priors $\mathcal{N}(0, 10^5)$ for all parameters. Posterior summaries using WinBUGS are given in Table 4.15.

Table 4.15: Posterior summaries of parameters for $p(I|A, E, F, G, H)$.

		Rwy-01		Rwy-02		Rwy-03	
		mean	sd	mean	sd	mean	sd
	$\alpha^i|data$	2833.0	144.9	3202.0	160.3	3367.0	129.3
E	$\beta_1^i|data$	4.94	9.68	0.42	11.56	4.01	9.80
F^{low}	$\beta_2^{i,low}|data$	118.9	159.2	279.8	141.6	209.9	117.7
F^{med}	$\beta_2^{i,med}|data$	431.7	113.7	558.2	132.9	717.4	122.8
G	$\beta_3^i|data$	-18.87	14.86	-42.66	18.72	-6.85	14.32
H	$\beta_4^i|data$	4.56	2.08	14.22	5.627	0.41	2.12

As we can observe, the remaining distance I is strongly influenced by the autobrake (F) and the difference between IAS and Vapp at threshold (G). The signs of the involved coefficients, $\beta_2^{i,low}$, $\beta_2^{i,med}$ and β_3^i, are consistent. Regarding the positive value of $\beta_2^{i,med}$, this yields that when the autobrake is selected at "Medium", the landing roll will decrease and, therefore, the landing distance will be reduced while the remaining runway will be increased. The same reasoning holds for $\beta_2^{i,low}$, although to a lesser extent. Regarding the negative value of β_3^i, this means that the greater the IAS at threshold, the greater the kinetic energy will be and, in consequence, more runway will be needed to reduce the aircraft speed to 80 kt. The other two variables, E and H, have minor relevance, except for H at Rwy-02. Regarding E, the remaining runway distance is increased by the maximum reverse thrust, as indicated by the positive sign of β_1^i. However, the influence of the maximum reverse thrust is not so determining as that of the autobrake system. In this sense, we should note that the reverse thrust is highly efficient at high speeds, but inefficient at low speeds. Finally, regarding the height at threshold (H), the positive value of β_4^i could be an indicator of the tendency of some pilots to pitch down before the threshold in order to try to touch down as soon as possible, what is called in the jargon as "ducking under". Theoretically, the threshold should be overflown at 50 ft. But, sometimes, especially at short runways, pilots would descend below the glide slope to have more landing distance available, increasing also the remaining landing distance. However, we should emphasize that when "ducking under" is performed incorrectly (e.g. due to a wrong perception of the height at threshold under visual operation), it could result in the opposite effect to that desired, i.e. in a reduction of the remaining landing distance. This is so because such maneuver increases the rate of descent, something which, in turn, entails the following consequences: (1) increase of aircraft speed; (2) reduction of induced drag; (3) increase of ground effect; and, ultimately, (4) increase of landing distance and reduction of remaining runway distance. In this sense, recommendations should be given in order to instruct pilots about excessive or inadequate use of "ducking under". Summarizing, the strongest influence on the remaining landing distance when the speed is reduced to 80 kt is the autobrake configuration (F) and, to a lesser extent, the difference between IAS and Vapp at threshold (G), although the latter is actually relevant only for runways 1 and 2.

As it is not possible to obtain a closed form expression for the required predictive distribution of $p(i|e,f,g,h,data)$, we assume the following sampling scheme for each runway, to obtain a sample from the predictive distribution

Algorithm 7: Sampling from $p(i|a,e,f,g,h,data)$ for runway a

For $\mathtt{k}=1$ to $\mathtt{N}$
- Sample $\mathtt{e_k} \sim \mathtt{p(e|a,d,data)}$, $\mathtt{f_k} \sim \mathtt{p(f|a,data)}$, $\mathtt{g_k} \sim \mathtt{p(g|d,data)}$, $\mathtt{h_k} \sim \mathtt{p(h|a,d,data)}$
- Set values for $\mathtt{f_k^{low}}$ and $\mathtt{f_k^{med}}$
- Sample $\alpha_\mathtt{k}^\mathtt{i} \sim \mathtt{p}(\alpha_\mathtt{k}^\mathtt{i}|\mathtt{a,data})$, $\beta_\mathtt{1k}^\mathtt{i} \sim \mathtt{p}(\beta_1^\mathtt{i}|\mathtt{a,data})$, $\beta_\mathtt{2k}^\mathtt{i,low} \sim \mathtt{p}(\beta_2^\mathtt{i,low}|\mathtt{a,data})$, $\beta_\mathtt{2k}^\mathtt{i,med} \sim \mathtt{p}(\beta_2^\mathtt{i,med}|\mathtt{a,data})$, $\beta_\mathtt{3k}^\mathtt{i} \sim \mathtt{p}(\beta_3^\mathtt{i}|\mathtt{a,data})$, $\beta_\mathtt{4k}^\mathtt{i} \sim \mathtt{p}(\beta_4^\mathtt{i}|\mathtt{a,data})$
- Compute
  $\mathtt{i_k} = \alpha_\mathtt{k}^\mathtt{i} + \mathtt{e_k}\cdot\beta_\mathtt{1k}^\mathtt{i} + \mathtt{f_k^{low}}\cdot\beta_\mathtt{2k}^\mathtt{i,low} + \mathtt{f_k^{med}}\cdot\beta_\mathtt{2k}^\mathtt{i,med} + \mathtt{g_k}\cdot\beta_\mathtt{3k}^\mathtt{i} + \mathtt{h_k}\cdot\beta_\mathtt{4k}^\mathtt{i}$

4.5.10 Illustrating the usage of the model

We have developed a sampling scheme to implement the above computations in Section 4.4. All the code has been written in `R` on a `Windows` platform. The results in this section have been obtained after generating samples of size 100,000 from the involved distributions. We have replicated the generating scheme 100 times.

First, we are interested in the overall probability of having a landing in which the remaining runway distance is less than 2,000 ft when the aircraft is slowed down to 80 kt, see Figure 4.7. As we have mentioned before, this is a precursor of the possibility of having a high risk of runway overrun at landing. After implementing the computations in Algorithm 1, we have obtained

$$\Pr(I < 2000) = 0.000216,$$

with an associated standard deviation $4.98 \cdot 10^{-5}$. Given the current operational load, this would mean that we should expect less than one landing with a high risk of runway excursion per year, at any of the three incumbent runways.

If we want to compute such probability conditional on any specific runway, we must use the sampling scheme of Algorithm 2. After doing so, we have obtained the results summarized in Table 4.16. We have included, in parenthesis, the corresponding standard deviation.

Table 4.16: Posterior probabilities $\left(\times 10^{-4}\right)$ $\Pr(I < 2000 | A = \underline{a}, data)$.

Rwy-01	Rwy-02	Rwy-03
3.35(0.59)	2.61(0.62)	0.31(0.087)

As we can observe, Rwy-01 has the highest risk of not having to decelerate the aircraft at 80 kt before reaching the last 2,000 ft. Compared with the other two runways, the probability of runway excursion in Rwy-01 is around 1.2 times greater than that for Rwy-02, and around 28 times greater than that for Rwy-03. In this respect, it must be taken into account that Rwy-01 is approximately 250 m shorter than Rwy-02 and 200 m shorter than Rwy-03. In addition, and according to expert opinion, Rwy-01 is the most complicated one from an operational point of view, as: (1) at this airport, the opposite runway to Rwy-01 is not equipped with an ILS and pilots have to proceed through a visual approach; (2) it has a slightly U-valley shape; and (3) adverse wind conditions are more usual than in the other two runways, as can be seen from Figures 4.9 and 4.10. In Figure 4.14, we have plotted the histogram of the posterior samples for each runway. We have indicated with a vertical dashed line the threshold distance of 2,000 ft.

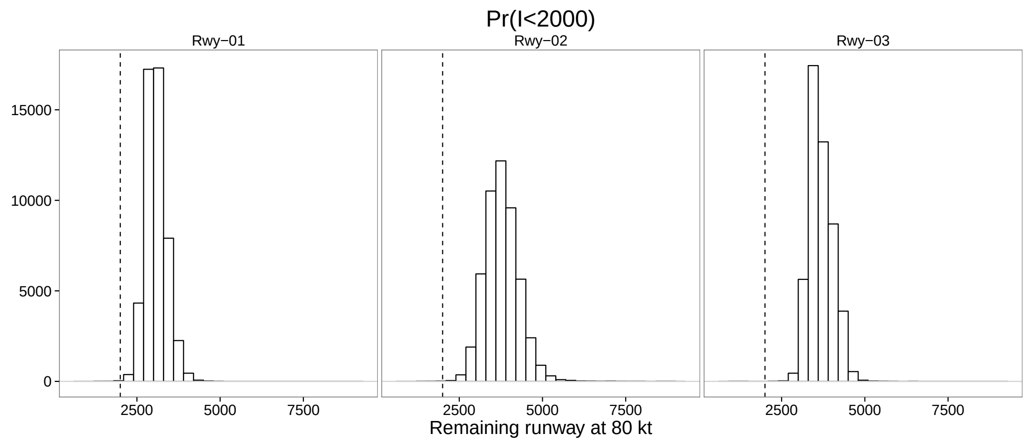


Figure 4.14: Posterior samples from $i|a, e, f, g, h$.

We deal now with the computation of such probabilities under severe wind conditions. Specifically, we consider the following cutoff cross and tailwind speeds, $\underline{b} \in \{10, 15, 20\}$ and $\underline{c} \in \{0, 5, 10\}$, as they are deemed relevant values by the experts. The maximum recommended cross and tailwind limits are based on aircraft manufacturers computation rather than on flight tests. However, these values are adjusted based on operational experience, and operators may reduce them for different reasons, e.g., during line training or initial line operation, see AIRBUS (2008). For the involved computations, we have made use of the samples generated with Algorithm 2, obtaining the results summarized in Table 4.17.

Table 4.17: Posterior probabilities $(\times 10^{-4})$ $\Pr(I < 2000|A = \underline{a}, B > \underline{b}, C > \underline{c}, data)$.

	Rwy-01			Rwy-02			Rwy-03		
	$\underline{b} = 10$	$\underline{b} = 15$	$\underline{b} = 20$	$\underline{b} = 10$	$\underline{b} = 15$	$\underline{b} = 20$	$\underline{b} = 10$	$\underline{b} = 15$	$\underline{b} = 20$
$\underline{c} = 0$	7.93	9.91	11.30	2.97	4.09	4.88	0.22	0.32	0.53
$\underline{c} = 5$	9.52	10.96	12.40	2.13	2.41	2.61	0.30	0.33	0.57
$\underline{c} = 10$	11.79	12.66	13.68	2.00	2.07	2.18	0.63	1.02	1.02

As we can observe, $\Pr(I < 2000|A = \underline{a}, B > \underline{b}, C > \underline{c}, data)$ tends to increase, in general, as the wind conditions worsen, i.e., as the cutoff values $\underline{b}$ and/or $\underline{c}$ increase. This seems reasonable, since landing under windy conditions tends to increase the probability of having an unstabilized approach, see Section 4.5.4. This, in turn, will affect the maximum reverse thrust (E), the difference between IAS and Vapp (G), and the height at threshold (H), see Figure 4.6. Under an unstabilized approach, these variables tend to have particular values, differentiated from the stabilized approach, see Sections 4.5.5, 4.5.7 and 4.5.8, and which might eventually increase the risk of having less remaining landing distance at 80 kt. However, Rwy-

02 is an exception to the previous reasoning, since the target probability tends to decrease as we increase the cutoff tailwind $\underline{c}$ (but not the crosswind). This can be explained by the negative value of β_2^d in Table 4.7, but we should also recall that we only had one operation under unstabilized approach for this runway, see Table 4.8, so no definitive conclusion can be drawn for this case. Having said this, and based on a similar reasoning to that of Section 4.5.4, we should also keep in mind that crews will become more aware when adverse weather conditions are present and, therefore, they will do their best to temper the influence of tailwind, especially when landing close to the limit $\underline{c} = 10$. Moreover, under severe wind conditions, e.g., $\underline{b} = 20$ and $\underline{c} = 10$, "going-around" and proceeding to the alternate airport would be the right decision.

We can also be interested in computing the likelihood ratios of runway excursion risk depending on whether the approach is unstabilized or not. After performing the computations in Algorithm 3, we have obtained the following likelihood ratios, summarized in Table 4.18.

Table 4.18: Likelihood ratios for D.

Rwy-01	Rwy-02	Rwy-03
8.65	12.92	2.49

These results suggest that much more dangerous conditions could arise under an unstabilized approach for all runways, a feature which is especially pronounced in Rwy-02. Recommendations should be given in that case in order to implement additional mitigation measures aiming at improving situational awareness at a given runway. For instance, an innovative measure could be to communicate this high risk level from the flight dispatcher to the flight crew, or to include a warning in the airports pilots briefing manual or arrival charts.

Another task of interest is assessing the risk of runway excursion given that the reverse has been operated at maximum thrust during a certain time, i.e., Pr$(I < 2000 | A = \underline{a}, E \leq \underline{e})$. We have set three possible cutoff values for the maximum reverse thrust usage during ground roll, $\underline{e} \in \{0, 5, 20\}$. Using the samples previously generated in Algorithm 2, we have obtained the results in Table 4.19.

Table 4.19: Posterior probabilities $\left(\times 10^{-4}\right)$ Pr$(I < 2000 | A = \underline{a}, E \leq \underline{e}, data)$.

$\underline{e}$	Rwy-01	Rwy-02	Rwy-03
0	0.38	0.20	—
5	1.32	0.54	0.009
20	1.69	0.85	0.015

Regarding the use of reverse thrust, this is an issue which is intimately linked with current policies to reduce fuel consumption. For this reason, and also due to noise abatement airport procedures, pilots are requested to operate reverse thrust at idle during ground roll, except when necessary for safety reasons. How long do pilots operate the maximum reverse thrust will depend on how fast the aircraft needs to be slowed down. In this regard, aircraft deceleration depends on several factors, as headwind/tailwind or its gross weight. As we can observe from Table 4.19, the longer the maximum reverse thrust has been operated, the higher the target probability. In other words, this may be an indicator that, at any given runway, if the full reverse thrust has been operated for too long, say over $\underline{e} = 10$ seconds, the aircraft might have experienced difficulties to decelerate during the ground roll, therefore risking a runway excursion.

Finally, we could be interested in assessing the likelihood ratios of runway overrun risk depending on the autobrake system setting. Specifically, we have computed such ratios comparing the “Low to None” (1–0) and “Medium to None” (2–0) configurations. To do so, we have implemented the computations in Algorithm 4, and obtained the likelihood ratios in Table 4.20.

Table 4.20: Likelihood ratios for F.

	Rwy-01	Rwy-02	Rwy-03
Low to None	1.02	1.11	0.79
Medium to None	1.05	1.14	0.84

As we can observe, the likelihood ratios are relatively close to one. Therefore, this would suggest that operating or not the autobrake system at these runways would not have, in principle, a significant impact on the probability of slowing down the aircraft speed at 80 kt beyond the last 2,000 ft. However, at Rwy-02, the probability of late deceleration of the aircraft is slightly higher when the autobrake system is used. The opposite is observed in Rwy-03, where the likelihood ratios are smaller than one. In this last case, this would possibly suggest selecting the autobrake system as an SOP recommendation for Rwy-03.

4.6 Conclusions

The safety event studied in this chapter falls within the group of most frequently reported accident types in the world. It can still be considered as a major threat to aviation safety. Runway excursions belong to the type of events occurring with very low probability but whose implications may be very severe. This constitutes an additional challenge for a risk analyst. Several international aviation organizations are focusing their efforts on reducing landing overruns, investigating various safety strategies.

We have used the information available from manufacturers, operators and safety agencies, expert judgement and data to propose an influence diagram which defines our probabilistic model. We have described a case study in which three runways with similar operational conditions have been selected. The critical event considered was $I < 2000$ and we have used $Pr(I < 2000)$ to assess the risk of runway excursion. From our case study, we have uncovered the following issues:

- Regarding operations with cross and tailwind components, data do not suggest strong correlation between them, in our specific case study.

- According to our model, landing under windy conditions, with crosswind and tailwind components, increases, in general, the probability of unstabilized approach, although the influence of tailwind is not so relevant at runways 2 and 3. According to expert opinion, this might be explained by the fact that when landing is under bad wind conditions, situational awareness increases and crews will follow SOPs strictly. Thus, in day-to-day windy landing operations, crews use to flight stabilized approaches, especially at short runways.

- The variables that were found to have the strongest influence on the remaining runway at 80 kt were the available landing distance, the autobrake system and the difference between the IAS and the Vapp at threshold. The maximum reverse thrust and the height at threshold seem to have a minor effect.

- Based on our model, and regarding height at threshold, we have demonstrated the "ducking under" effect, i.e. the tendency to pitch down before the threshold to have more landing distance available.

- The results show that the probability of decelerating the aircraft at 80 kt in the last 2,000 ft of the runway increases, in general, as the tail and crosswind components increase. Rwy-02 is an exception for this trend, since such probability decreases with the value of the cutoff tailwind, but few conclusions can be drawn in this case, since only one operation took place under an unstabilized approach for this runway. Regarding the results with respect to crosswind, they are consistent with day-to-day operations since, under strong crosswind, it is more difficult to control and decelerate the aircraft on ground simultaneously. For this reason, it is recommended to select the autobrake system in the presence of crosswind.

- As accidents of runway excursions reports highlight, our model suggest that much more dangerous conditions could arise under unstabilized approaches.

- Finally, we have observed that the longer the maximum reverse thrust has been operated, the less remaining runway at 80 kt, therefore facing a higher risk of runway excursion. Thus, if the maximum reverse thrust has been operated for too long, this may be an indicator that, at any given runway, the aircraft might have experienced difficulties to decelerate during the ground roll. This variable could then be used as a runway excursion risk precursor, a relevant information for airlines Flight Data Monitoring (FDM) teams.

Chapter 5
Conclusions and Future Research

5.1 Introduction

The combination of the likelihood and the consequence of a negative outcome leads to the concept of risk. If we were able to predict exactly the future behavior of a system, risk would disappear. Recent years have seen significant advances in the use of risk analysis in several fields, being the nuclear sector a good example. However, in the commercial aviation domain this has not been fully integrated yet within the operations management structures. According to Bedford and Cooke (2007), in the aerospace sector a systematic concern with the risk assessment methodology began after the fire of the Apollo test AS-204 on January 27th, 1967, in which three astronauts were killed. This event involved considerable loss of public support, costed National Aeronautics and Space Administration (NASA) salaries and expenses for 1500 people involved in the subsequent investigation, and ran up to USD 410 millions in additional costs. Prior to the Apollo accident, NASA had traditionally relied on its contractors to apply "good engineering practices" in order to provide quality assurance and control. However, since the Shuttle accident, NASA has instituted programs of quantitative risk analysis to support safety during the design and operation phases of manned space travel.

Nowadays, risk analysis is applied to many different fields, see Bedford and Cooke (2007), but we have focused in this Thesis on risks associated with the operation of complex safety-critical systems such as commercial air transport of passengers where undesired events during operation can lead to catastrophic losses. We shall draw in what follows our main conclusions about:

- A general overview about operational safety and risk management in commercial air transport operations.

- A risk analysis model for a relatively frequent event in air transport safety: unintentional slide deployment under commercial airline normal operations.
- A risk analysis and decision-making model for the fueling for holding problem for delayed approaches at congested airports.
- A risk analysis model for a major threat to aviation safety: the Lp/Hc event of runway overrun excursion at landing.

Finally, we shall present some additional hazards and research issues for the air transport industry which could be worth considering for future research, mainly in relation with developing new risk models.

5.2 Relevant results

First, we briefly outline some of the most important features we have discussed throughout this Thesis.

5.2.1 A general overview about operational safety and risk management in commercial air transport operations

Air transport is one of the safest ways of traveling. In 2013, more than 3 billion passengers will travel by air, almost double than in 2001. According to IATA (2013b) predictions, this number will be doubled by 2030. In 2012, the global Western-built jet accident rate (measured in hull losses per million flights) was 0.20, equivalent to one accident every 5 million flights. This represented a 46% improvement over 2011, when the accident rate was 0.37, or one accident every 2.7 million flights. Nevertheless, it is essential to continuously improve such level of safety for the benefit of society. Since 2003, the accident rate has been relatively steady. The rate of fatal accidents has not improved significantly, averaging between 4 and 5 fatal accidents per 10 million flights. Vasigh et al. (2008) consider that the economic equilibrium between the benefits and costs of safety could have been reached. In any case, and given that the costs of incident/accidents could be so high for airlines, understanding the total costs of these events is fundamental to acknowledge the economics of safety. The benefits of safety are undeniable, not only from a moral standpoint, but also from an economic point of view, as reflected in strengthened consumer demand and labor supply, reduced insurance costs, lower cost of capital, lower liability risk, reduced costs associated with government fines or penalties, among others.

It seems clear that safety thinking has experienced a significant evolution over the last fifty years. Despite the fact that expressions like "safety must be preserved at any price" are commonly used, since a few years ago, safety is increasingly viewed as a risk management issue, and it has been judged within the economic context of cost-benefit analysis, where increases in safety are optimal only when the safety benefits justify the costs. Moreover, the current perspective is that safety is not the first priority of aviation organizations. In this respect, IATA issued a call to balancing risk and regulation, stating that 100% free-risk policies are not acceptable, and any regulation that would eventually eliminate risk would shut the industry down. A pragmatic approach is then needed, see IATA (2013b). According to it, safety management is just another organizational process that allows aviation organizations to active their business objectives through their delivery of services. This new point of view is supported by ICAO through the regulatory framework of the Safety Management System (SMS), see ICAO (2009). Resource allocation must be balanced to ensure that the company is protected while it keeps producing. However, what accident investigations show is a tendency for organizations to drift into the allocation of resources in detriment of safety. In these organizations, it is a matter of time that such decision making policy will eventually lead to a catastrophe. Moreover, various authors argue that there is no demonstrable safety improvement that can be directly attributable to the SMS, see e.g. Thomas (2012). This could be attributed to current ICAO risk management, in which safety is defined in a simplistic way with little detail and a poor scientific framework. Therefore, a new approach supported by a solid scientific basis would be more appropriate. In this regard, we have proposed a framework to perform risk analysis and decision-making that might be applied to other particular aviation events or other modes of transportation.

Other industrial and technological sectors, as the nuclear, have made the largest commitments of resources in the area of risk methodologies, especially in the probabilistic risk analysis field. In the aerospace sector, however, the methods have not yet been fully integrated into the existing design and operations management structures, see Bedford and Cooke (2007). Besides, the predominant mode of treating human contributions to reliability of complex well-defined systems is to consider humans as a hazard. Another perspective which has been relatively little studied considers humans as a system element whose adaptations and compensations have brought troubled systems back from the brink of disaster on a significant number of occasions, see Reason (2008).

In the same manner as risk management, risk communication is a relatively new field. Risk communication must provide the essential links between analysis, management staff and the rest of the organization. For this reason, it is a critical component of the whole process. As a simple communication tool, risk matrices have been adopted in aviation, see ICAO (2009). Cox (2008) argue that risk matrices experience several problematic features making it harder to asses risks. Furthermore, from an organizational perspective, an important disadvantage of risk matrices is that assessing risk through its use could turn the safety process into a “paper safety”, providing a false sense of safety to the organization. Poor risk assessment can contribute significantly to poor decision-making and the latter has been implicated as a leading factor in fatal aviation accidents, see Jensen (1977).

Consequently, due to the huge increase expected in the number of passengers, industry needs to keep on reducing the aircraft accident rate, specially in some regions of the world. This can be achieved through new approaches and tools for safety.

5.2.2 A risk analysis model for unintentional slide deployment

According to certified standards, each non-over-wing emergency exit higher than 1.8 m (6 ft) from the ground must have an approved mean to escape from the aircraft to the ground level during emergencies. However, every year many of these emergency slides are unintentionally deployed under normal operations, becoming a safety risk with relevant economic implications

We have provided a formal risk analysis for this problem, focusing on economic impacts, due to the lack of reported data concerning injuries over the period of interest. Unlike standard practice in this field, and under a Bayesian approach, our analysis is based as much as possible primarily on historical recorded data, relying on expert opinion to fill the gaps when data is unavailable. Upon discussion with experts and a review of the existing literature, we have identified several factors potentially affecting unintended slide deployment under normal operations. We first assessed the entailed risks providing a model for the occurrence of such incidents and its associated costs, and combined them to provide forecasts for the corresponding total costs. Based on our model, the tests performed and brainstorming sessions with airline experts, we devised several possible countermeasures. Afterwards, we have assessed and selected the optimal countermeasure within the economic context of a cost analysis, where increases in safety are optimal only when the safety benefits justify the costs. As implementing only one countermeasure is rarely sufficient to avoid incident or accident to occur, we have proposed not only technical solutions, but also other countermeasures, such as procedure revisions. In a period of one year elapsed since these countermeasures were implemented, the number of deployments was hugely reduced to nearly 75%. On account of this, not only the safety level was increased due to our recommendations, but also the delay time was reduced, improving the quality of service perceived by the passengers. Based on this risk analysis approach, we have demonstrated that there are many other relevant aviation risks, specially during passenger boarding and aircraft taxiing phases, that might benefit from an approach similar to the one described here.

5.2.3 A risk analysis and decision-making model for the fueling for holding problem

Fuel accounts for more than 25% of the annual operating costs for airlines. In a competitive environment and with increasing fuel costs, air carriers are looking for ways to improve fuel efficiency without putting flight safety into jeopardy. Currently, one of the main reasons for holding at destination is traffic congestion. When delays occur during the approach flight phase, holding may be required by ATC, but the flight crew will be able to hold depending on the remaining fuel quantity. In order to appreciate the scale of the problem, a short-medium aircraft type will burn more than 1 ton of fuel after holding 30 minutes. Inability to hold, because of a fuel shortage, will cause the flight to divert to an alternate airport. This situation entails significant DOC for the company, specially for those airlines with hub-and-spoke model.

Fueling for holding is not a simple decision and has become an important issue given the increasingly frequent busy airports. A modern aircraft burns between 3% to 4% of additional fuel carried per hour of flight, so excessive fuel on board may have a significant impact in the balance account. A good understanding of this problem can help airlines, not only to operate fuel more efficiently, but also to better deal with low fuel events. As a consequence, it seems important to provide models to support decisions about the optimal fuel quantity for holding, looking for a balance between fuel costs and other operational costs arising as a consequence of diverting to the alternate airport. The traditional approach to such decision is to fuel aircraft with an additional fuel quantity if there is information about delays, without modeling and assessing other potential costs. In this respect, we have provided a decision analysis model based on a continuous decision tree, as viewed from the perspective of the company, illustrating the decision-making process in two different scenarios. The first concerns a long-haul flight which is operated with a four engine wide-body aircraft. The second one is a short/medium-haul flight which is operated with a two engine narrow-body aircraft. Finally we have proceeded with optimization aiming at minimizing expected costs. The proposed model could be turned into a decision support system for any specific aircraft type and airport of the airline network. Key issues within our model are a thorough analysis of the involved cost distributions as well as a detailed forecast model of such delays. With our case studies, we have proved the need for integrating different airline divisions to analyze and assess operational costs, such as fueling, delays or airport diversions in a global manner. The need for having decision models related with passenger delay costs, which are difficult and complex to quantify; and furthermore, that DOCs can be considerably reduced.

5.2.4 A probabilistic risk model for runway excursion at landing

Runway overrun at landing constitutes a top safety event for regulatory agencies and the entire commercial aviation industry as it accounts for approximately 25% of all incidents and accidents. While its occurrence rate is very low, the entailed consequences may be very severe. For example, from 2005 to 2007, Bateman (2009) calculated that runway excursion costs amounted to about USD 500 million per year. New safety technologies that reduce runway risk are being developed, focusing on human-factors-driven flight deck design enhancements. However, they need to be practical and cost effective to be accepted.

Today's commercial aviation is operating at such a high level of safety that breakthroughs in safety improvement will be hard-won, and will require deeper levels of analysis and increasingly sophisticated tools and methods. Existing methods and models are useful but new perspectives can add further insights to enhance safety, see Luxhøj and Coit (2006). Therefore, for this relevant safety issue, we have described a probabilistic risk model. Due to the multiple contributing factors associated with runway overruns, and in order to visualize the relevant ones, we have designed a mind map based on several studies and expert judgement techniques. Following that, we have built a probabilistic influence diagram, based on the information from manufacturers, operators, safety agencies, expert judgement and data available. According to the FSF, our key variable was the remaining runway at 80 kt. Our model aims at assessing the risk at a given runway under various conditions, providing a comparison of various runways or airports in terms of the probability of excursion, as a way to show potentially more dangerous runways. This may point towards cases in which special mitigation measures need to be taken into account. We have discussed the use of such model with a case study in which we have identified some interesting finding, as e.g.: crosswind and tailwind have not a significant influence on the probability of unstabilized approach, nor have influence in the remaining landing distance, but however, the available landing distance, the autobrake setting or the indicated airspeed when overflying the threshold have found to have a strongly influence on the landing distance.

5.2.5 General comments

Besides the specific comments for each case study, other relevant general considerations regarding the whole scope of risk analysis in the airline industry emerge from this thesis:

- Safety thinking has experienced a significant evolution and is currently viewed as a risk management process.

- Various authors argue that ICAO risk management is defined in a simplistic way, with little detail and poor scientific framework, see e.g. Thomas (2012). Moreover, empirical evidence has not yet provided a significant demonstrable safety improvement that can be directly attributable to SMS. Our aim has been to improve such situation.

- Since 2003, the accident rate has been relatively steady, which might be due to the fact that an economic equilibrium between safety benefits and costs could have been reached. A better understanding of the total costs of incidents and accidents, and in general, the economics of safety is needed. Again, we have emphasized such analysis.

- As in the case of unintentional slide deployments, there are certain events with not so significant potential safety risk but with relevant economic implications. This is the case of some ramp incidents/accidents such as aircraft ground damages. For this kind of events, we have assessed and selected the optimal countermeasure within the economic context of an expected utility analysis. Our case study might be also useful not only for safety issues but to assess the modification of operational procedures.

- A good understanding of the fueling for holding at destination due to delay can help airlines not only to operate fuel more efficiently but also to better deal with low fuel events. With our case studies, we have proved the need for integrating the different airline divisions to analyze and assess operational costs, and the need for having decision models related with passenger delay costs.

- Aviation incidents/accidents are distinguished for being Lp/Hc events. However, as the expected number of passengers in 2030 will be double with respect to the current levels, it seems clear that a continuous improvement in safety is needed. To achieve this, proper event modeling processes specific for aviation, will become imperative, and new scientific frameworks and robust inference methods will be needed. In this respect, a Bayesian-based methodology has been demonstrated useful.

5.3 Future research

"Aviation today is a global mass transit system for nearly 3 billion people and 50 million tons of cargo. This is a critical component at the foundation of our global community", said Tony Tyler, IATA Director General and CEO, in June 2012. Aviation will not be able to deliver this huge business without assessing and managing current and future hazards. Moreover, today's commercial aviation is operating at such high level of safety that breakthroughs in safety improvement will be hard-won, and will require deeper levels of analysis and increasingly sophisticated tools and methods. Existing methods and models are already useful, but new perspectives, as those in this thesis, can add and enhance safety. Up to now, even the best safety analyses were forensic in nature. Safety improvement was characterized by a fly-crash-fix-fly approach. We would fly airplanes, have the occasional unfortunate crash, and would investigate the causes to prevent it from happening again, see Stolzer et al. (2008). In our days, the aviation community has realized that it is more efficient to develop systems in which causes of failure are detected and mitigated up to a reasonably risk level.

Thus, new models and more sophisticated Decision Support Systems will be needed. They will have a vital role in the future air transportation system, helping airlines to better manage the high number of operational and commercial threats and maximizing revenue opportunities. Moreover, the aviation industry and technology are changing but it looks as if these changes are not being reflected in our safety approaches. As established by Leveson (2009), most of the safety engineering techniques and tools we use today were originally created first for mechanical, and later, electro-mechanical systems. They rest on models of accident causation that were appropriate for those types of systems, but not for the majority of the systems we are building today, specially in aviation technology. Some authors, see e.g. Leveson (2009), suggest that in order to make significant progress in safety, we need to rethink the old models and create new accident causality models, as well as engineering techniques and tools based on them that include, not only the old incident/accident causes, but also the new types of events and causality factors. In addition, given that systems safety involves spending money in order to reduce the probability and consequences of accidents, moral and economic questions inevitably arise concerning the amount of money that should be spent on safety, see Dale and Anderson (2009). Therefore, we should consider not only discussing such controversy, but also use criminal law as a tool for improving safety, see Fisher (2009).

In what follows, we propose some directions for future research work in the area of risk analysis in aviation operations.

5.3.1 New incident/accident causation models

After computers and other Information and Communication Technology (ICT) became important in most new systems such as aircrafts or AFTM control systems, the primary approach to handling safety has been trying to extend traditional techniques and tools to include software and hardware. Software allows engineers to increase the interactive complexity and coupling of systems such as the sophisticated flight control computers implemented in new aircraft models, see Figure 5.1.

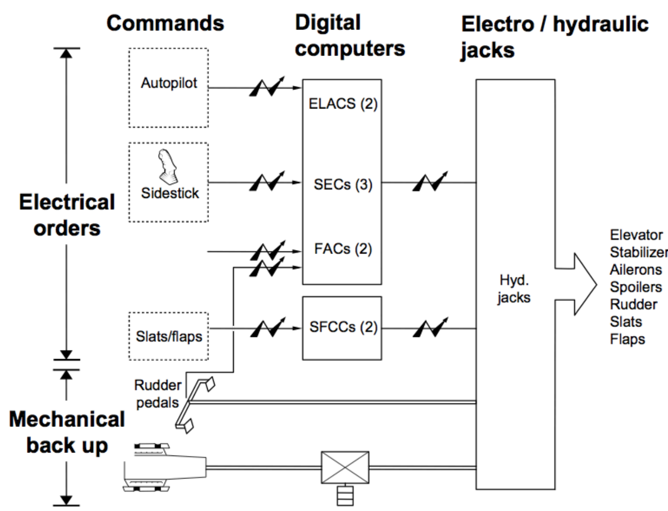


Figure 5.1: A320 Flight Control System. Source: Airbus

The new types of incidents or aircraft accidents that are occurring do not fit within the traditional accident causation model. As an example, the loss of the Mars Polar Lander was attributed to a spurious signal generated when the landing legs were deployed. This noise was normal and expected but the onboard software interpreted such signals as an indication that landing occurred and shut the engines down causing the spacecraft to crash into Mars surface. The software thus performed correctly with respect to the specified requirements.

These new accidents arise not from the failure of individual system components, but from dysfunctional interactions among components, none of which would have failed individually. According to Leveson (2009), traditional accident causation models explain accidents in terms of chain of events that leads to the accident. The relationships between different events in the chain are assumed direct and relatively simple. Using this causation model, the most appropriate approaches to preventing accidents is to somehow “break the chain” by, either preventing an event, or by adding additional “and” gates in the chain to make the occurrence of events in the chain less likely. However, incidents or accidents can result from interactions among subsystems that violate systems safety constraints. Furthermore, traditional models of accident causation treat the system as static, and systems are continuously changing. All these simplifications limit our ability to prevent or detect system migration to a higher risk state. Moreover, as Leveson (2009) mentions, such models are limited in their ability to handle accidents in complex systems, understanding organizational and managerial (social and cultural) factors in accidents, and incorporating human error models and the systemic causes of events.

5.3.2 Risk modeling for cyber-terrorism and malware attacks

One of the main conclusions following the events of September 11, 2001, was that aviation terrorism risk was difficult to assess. Even worse, in the near future, aviation terrorism could appear in difference ways unknown so far, as e.g. “cyber-terrorism”. Commercial aircraft, currently rely heavily on fully automated flight decks and other flight entertainment systems. This could allow a hacker with a laptop to attack the system from his/her seat, or, maybe in the future, from ground.

On March 28, 2003, Boeing applied for an FAA type certificate for its new 787 passenger airline. It was an all-new, two engine jet transport airplane with a two-aisle cabin with a maximum passenger count of 381, see Figure 5.2.

Figure 5.2: Boeing Model 787. Source: Boeing

In 2008, this new commercial jet airplane was denied certification by the FAA due to dangerously unregulated computer systems like the in-flight internet system provided to passengers. The airplane manufacturer was required to fulfill special conditions before the aircraft could become certified proving that its passenger entertainment systems was prevented from actively accessing data networks connected with the airplane systems that perform functions required for safe operation.

Figure 5.3: B 787 Flight Deck. Source: Boeing

This airplane has novel and unusual design features when compared to the state of technology envisioned in airworthiness standards for transport airplanes. These features are associated with connectivity of the passenger domain computer systems to the airplane critical systems and data networks. Current applicable airworthiness regulations do not contain adequate or appropriate safety standards for protection and security of airplane systems and data networks against unauthorized access, see FAA (2008b). The digital systems architecture for the 787 consists of several networks connected by electronics and embedded software. This proposed network architecture is used for diverse functions including:

- Flight-safety-related control and navigation and required systems (Aircraft Control Domain).
- Airline business and administrative support (Airline Information Domain).
- Passenger entertainment, information, and Internet services (Passenger Information and Entertainment Domain)

The proposed architecture is different from that of existing production (and retrofitted) airplanes. It allows new kinds of passenger connectivity to previously isolated data networks connected to systems that perform functions required for the safe operation of the airplane. Because of this, the proposed data network design and integration may result in security vulnerabilities from intentional or unintentional corruption of data and systems critical to the safety and maintenance of the airplane. The existing regulations and guidance material did not anticipate this type of system architecture or electronic access to aircraft systems that provide flight critical functions. Furthermore, Certification Flight Rules Regulations and current system safety assessment policies and techniques do not address potential security vulnerabilities that could be caused by unauthorized access to aircraft data buses and servers. Therefore, special conditions were imposed to ensure that security, integrity and availability of the aircraft systems and data networks was not compromised by certain wired or wireless electronic connections between airplane data buses and networks, see FAA (2008b).

5.3.3 Rethinking human reliability analysis methodologies

As established by French et al. (2011), few systems operate completely independently of humans. Thus, any study of system risk or reliability requires analysis of the potential for failure arising from human activities in operating and managing this. Moreover, the role of human operators is changing from direct control to supervisory positions involving sophisticated decision-making processes, see Figure 5.4. Therefore, the types of mistakes humans are making are different and are not readily explained or handled by traditional chain-of-failure-events models, see Leveson (2009).

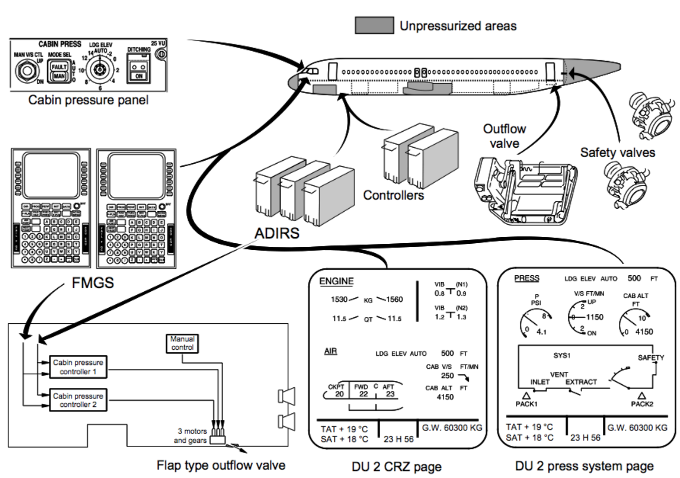


Figure 5.4: A320 Cabin Pressure Control System. Source: Airbus

In spite of the fact that the history of the human reliability field may be traced back to the late 1950s, the beginning of serious thinking about human reliability or error in transportation systems goes back only to the late 1980s. Since the late 1950s, concerted efforts to reduce the accident rate in aviation have yielded unprecedented levels of safety. Although the overall accident rate has declined considerably over the years, reductions in human error-related accidents in aviation have unfortunately failed to keep pace with the reduction of accidents due to environmental and mechanical factors, see Dhillon (2007). Today, it is generally accepted that a very large percentage of all aviation accidents (over 70%) are attributable, directly or indirectly, to some form of human error. In well-defended systems, as air transport is, the predominant mode of treating human contribution is to consider humans as a hazard, a system component whose unsafe acts are involved in the majority of incidents or accidents. According to Reason (2008), we know far more about the hazardous human than day-to-day situations in which operators recover the system, avoiding catastrophic breakdowns, due to the fact that most observations of human operators in high-risk systems are obtained from well-documented accident investigations. This author proposes a human error perspective that has been comparatively little studied, which consists of looking at the human factor as a system element whose adaptations and compensations have brought troubled systems back from the disaster on a significant number of occasions. In addition, together with this classical vision of human error, we should consider that although a large proportion of the accidents can be attributed to human error, many accidents are catalyzed by persons not present at the time of the event. This is the source of latent conditions that pose a most significant threat to the safety of complex systems.

In this context, good risk perception models in aviation that fully integrate the human contribution on general decision-making models under risk, are needed, as risk perception and risk tolerance are two factors that can significantly impact decision-making. Inaccurate risk perception can lead to ignore or misinterpret external cues that demand immediate and effective decisions to avoid hazards. High risk tolerance can lead to choose courses of action that unnecessarily expose them to hazards and increased likelihood of accident. Data of pilots visiting a government web site showed that risk perception demonstrated a small, but significant, correlation with self-reported involvement in hazardous aviation events, and, contrary to expectations, risk tolerance was not significantly related with hazardous events, see Hunter (2002). French et al. (2011) affirm that no method has yet been developed which incorporates all our understanding of individual, team and organizational behavior into overall assessments of system risk or reliability. They have explored these issues, concluding that:

- No single Human Reliability Analysis (HRA) is likely to suit all purposes and contexts.

- The range of theoretical bases for modeling human reliability needs to be extended to take into account recent findings in human cognition and behavior, as well as organizational effects on performance.

- Much more comparative research is needed on the coherence, strengths and weaknesses of different HRA methods proposed to date.

Only by accomplishing this, we will be able to build comprehensive system risk and reliability analysis in which a reasonable degree of trust may be placed.

5.3.4 Economic modeling of safety and aviation security

Since the terrorist attacks on September 11, 2001, aviation security policy has become a priority for governments and the resources for this issue have been substantially increased. Besides, mathematical models have been developed to address some prominent problems in aviation security, and guiding policy-makers in adopting security measures, by helping them to identify most the crucial parameters concerning the effectiveness of aviation security policies, see e.g. Martonosi (2005). Despite the fact that many people claim that safety and security should be maximized regardless of the cost, currently, aviation organizations must deal with the "dilemma of the two Ps", protection versus production. According to Vasigh et al. (2008), to understand the economics of aviation safety, one needs to look at the industry from the macro-level, where the benefits of safety regulations to consumers and companies are weighed against the costs of imposing the regulations. Many safety regulations enacted by governments are blanket responses to potential threats, or media-generated reactions that merely alleviate passenger concerns, while actually not increasing safety in any substantial way. An example of this would be all the procedures regarding to boarding passengers while refueling the aircraft, or regulation banning aircraft push-back until all passengers are seated, which was created in part as a response to other airlines lobbying against Southwest practices, see Vasigh et al. (2008). Without a proper risk analysis or a proper decision-making model, there is a strong probability that a number of aviation safety regulations generate more costs than benefits. As established by Vasigh et al. (2008), it is probably true that if one were to perform the economic analysis for all safety regulations, many would pass due to the substantial benefits from improved safety. However, some regulations would also fail, largely because they were enacted in response to political pressure. Eliminating some costly regulations that do little to improve safety should reduce ticket prices, draw people away from other transportation systems to aircraft, and thus, improving net safety in society.

Thus, as Vasigh et al. (2008) state, we could increase total safety by some deregulation degree regarding airline safety. Due to the difficulty in assessing the value of incidents or accidents that have not occurred or have been prevented, the costs of safety are even more difficult to quantify than the costs of accidents. Some studies have suggested rough incident and accident estimated costs, in which a number of assumptions have been made, due to the lack of data. Performing a safety cost-benefit is complicated partly because of the lack of proper economics commercial airline safety models.

5.3.5 Further comments

As a conclusion, we summarize directions for future research.

- Some types of current incidents or aircraft accidents that are occurring do not fit existing analysis methods and models. Moreover, in the coming years new hazards to aviation, difficult to assess nowadays, could appear. For example, a passenger could attack the avionic system of a commercial aircraft through the in-flight entertainment systems, giving rise to an emergency scenario. Therefore, new perspectives, deeper levels of analysis and more sophisticated tools can add further enhance safety.
- Few systems operate completely independently of humans. Moreover, the role of human operators is changing, and therefore, the types of mistakes humans are making are different. In this context, there is a need of researching how to integrate the human contribution into new risk models. To achieve this goal, good risk perception models are required and need to be incorporated.
- Due to the difficulty in assessing the value of events that have not occurred or have been prevented, the costs of safety are even more difficult to quantify than the costs of accidents. However, it has been demonstrated that there is a need for researching in economic modeling of safety and aviation security. In addition, this will be very helpful in assessing mitigation measures during the decision-making process.

The importance of the aviation business in our globalized economy clearly make all these worthy of being pursuit.

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