UNIVERSIDAD POLITÉCNICA DE MADRID
ESCUELA TÉCNICA SUPERIOR DE INGENIERÍA AERONÁUTICA Y
DEL ESPACIO

DEVELOPMENT AND VALIDATION OF A SAFETY MODEL IN
PREDICTING ACCIDENTS / INCIDENTS IN THE AIR TRAFFIC
MANAGEMENT SYSTEM

*Desarrollo y Validación de un Modelo de Seguridad en Predecir los
Accidentes / Incidentes en el Sistema de Gestión del Tránsito Aéreo*

TESIS DOCTORAL / DISSERTATION

Schon ZhengYu Liang Cheng

Ingeniero Aeronáutico / M.S. Aeronautical Engineer

Madrid 2019

DEPARTAMENTO DE SISTEMAS AEROESPACIALES, TRANSPORTE AÉREO Y
AEROPUERTOS

ESCUELA TÉCNICA SUPERIOR DE INGENIERÍA AERONÁUTICA Y DEL ESPACIO

Título: DEVELOPMENT AND VALIDATION OF A SAFETY MODEL IN PREDICTING
ACCIDENTS / INCIDENTS IN THE AIR TRAFFIC MANAGEMENT SYSTEM

DESARROLLO Y VALIDACIÓN DE UN MODELO DE SEGURIDAD EN PREDECIR
LOS ACCIDENTES / INCIDENTES EN EL SISTEMA DE GESTIÓN DEL
TRÁNSITO AÉREO

Autor:

Schon ZhengYu Liang Cheng

Ingeniero Aeronáutico / M.S. Aeronautical Engineer

Director de Tesis:

Rosa María Arnaldo Valdés

Doctor Ingeniero Aeronáutico

Madrid, 2019

Tribunal nombrado por el Sr. Rector Magfco. de la Universidad Politécnica de Madrid, el día.....de.....de 20....

Presidente:_____

Vocal: _____

Vocal:_____

Vocal:_____

Secretario:_____

Suplente:_____

Suplente:_____

Realizado el acto de defensa y lectura de la Tesis el día.....de.....de 20 ...
en la E.T.S.I. /Facultad.....

Calificación

EL PRESIDENTE

LOS VOCALES

EL SECRETARIO

SHELL

*In memory of my grandfathers,
the first generation of engineers in this family*

ACKNOWLEDGMENTS

Llegado a este punto, es un buen momento de echar un ojo hacia el pasado. Primero de todos, gracias a mis padres por sus sacrificios en el pasado para que pueda yo llegar hasta aquí en este presente. Como miembro de la familia, gracias a Jing Yang, fundador de Bonjour Shainghai Agence de Communication, por su diseño en algunas ilustraciones.

Personalmente, me gustaría hacer una dedicatoria a Carlos López y Claudio Kirkpatrick, sin vosotros no podría ni entrar en este mundo de ingeniería aeronáutica, gracias por vuestro pleno soporte en ayudarme mover las montañas que obstaculizaban mi camino.

A lo largo de estos años de carrera en el mundo aeronáutico, he conocido y compartido buenos momentos tanto personales como profesionales con muchos ingenieros aeronáuticos cualificados. Especialmente mis amigos de la antigua ETSIA, siempre han estado en mi lado compartiendo lo malo y lo bueno. Entre ellos hay dos personas que me han influido en emprender este camino de la tesis. A Sven Lazan, si no por su aquel artículo de aplicar las redes neuronales en estimar los tiempos computacionales de correr los modelos fluidodinámicos, no podría lograr mi interés en tener otras visiones sobre la inteligencia artificial aplicada en la ingeniería aeronáutica. A Ricardo Román, al decir la verdad, ha sido quien me ha llevado a este mundo de navegación aérea, otro mundo igual de maravilloso que el de aeronaves.

A lo largo de mis años profesionales, he estado trabajando en diferentes empresas (ITP, Atos y Altran) y he tenido las oportunidades de colaborar con otras (Airbus Operations y Airbus Defence and Space). Con mis compañeros he adquirido y desarrollado nuevas habilidades, me han mostrado mundos nuevos, y juntos hemos estado navegando dentro de ellos. He aquí quisiera hacer una mención particular al departamento de certificación operacional de Altran y de Airbus Defence and Space. Especialmente, a Cristina Martínez y a Javier Poncelas, he aprendido mucho con ellos sobre los temas de la aeronavegabilidad y de la certificación. Estos conocimientos me han permitido completar el capítulo 7.

Durante el desarrollo de esta tesis, he tenido ocasiones de intercambiar ideas con gente profesional en el sector de navegación aérea. Gracias a D. Luis Mijares y D. Antonio Peláez de SENASA por concederme sus tiempos en escuchar mis ideas y proporcionarme ciertos materiales de soporte que han contribuido una parte de esta tesis. Adicionalmente, agradezco a Eva Puntero de CRIDA, por escuchar mis ideas y compartir sus experiencias contigo en diversos temas relativas a esta tesis.

También he tenido tiempo de conocer mejor el departamento SATAA de forma personal y profesional. A los miembros de este departamento, gracias por sus paciencias en aceptarme y compartir sus conocimientos conmigo. Particularmente, agradezco profundamente a Dr. Victor Fernando Gómez Comendador, por tenderme su mano en una época difícil que se ha cruzado con mi trayectoria profesional.

Por último y lo más importante, agradezco profundamente a Dra. Rosa María Arnaldo Valdés, por su dirección y paciencia a lo largo del desarrollo de este trabajo de investigación. Me ha dejado la libertad de comprobar mis ideas propuestas y, en ocasiones, me ha iluminado el camino antes de meterme en un jardín imperial. También quiero darle las gracias por todo lo que ha hecho por mí en los momentos difíciles de mi etapa profesional, nunca lo voy a olvidar.

Schon Z.Y. Liang

Madrid

Diciembre, 2019

ABSTRACT

The demand for air traffic has shown significant growth in the last ten years, and the capacity of airspace has presented the signal of saturation to respond efficiently to this increase in air traffic volume. For this and many other reasons, developments of more complex and sophisticated new air traffic management systems, such as the SESAR programme in Europe, have been launched to meet future needs. New technologies must not only provide improvements in future operations but most importantly, they should reduce the risks to incidents, even accidents, that can occur nowadays. In the present, current systems, before being upgraded, remain our last defences in preventing accidents and incidents. Therefore, we must understand their operational deficiencies or failures that still exist, thus taking measures to prevent undesirable occurrences.

According to EASA and EUROCONTROL reports of the last ten years, air traffic accidents have been drastically reduced, but the incidents have had a significant boom. In particular, incidents due to separation between aircraft have been classified as one of the categories of incidents with the highest risk and priority to be resolved.

Approaching this direction, this research work has focused on analysing incidents of loss of separation, along with reports published by CEANITA, with the intention of modelling their causes using statistical methods. From there, predictions are carried with the support of modern mathematical methods to identify possible critical scenarios of incidents or even accidents of Mid-Air Collision.

In addition, two other points of interest in development: i) the risk matrix is reviewed and modified to assess the evolution of the criticality of incidents; ii) Heinrich's Pyramid Theory is applied to propose a more sophisticated prediction model.

INTENTIONALLY LEFT BLANK

RESUMEN

La demanda del tráfico aéreo ha demostrado un crecimiento importante en los últimos diez años, y la capacidad del espacio aéreo ha presentado la señal de saturación para responder de forma eficiente a este aumento de volumen del tráfico aéreo. Por este motivo, y otros tantos, se han puesto en marcha los desarrollos de nuevos sistemas de gestión del tránsito aéreo más complejos y sofisticados, como el programa de SESAR en Europa, para satisfacer las necesidades futuras. Las nuevas tecnologías no sólo deben prestar las mejoras en las operaciones futuras, sino lo más importante, deben reducir los riesgos a incidentes incluso accidentes que pueden suceder actualmente. En el presente, los sistemas actuales, antes de ser renovados, siguen siendo nuestras últimas defensas en evitar los accidentes e incidentes. Por lo tanto, debemos entender las deficiencias o fallos operacionales que aún existen y, de esta manera, tomar las medidas en prevenir los hechos no deseados.

De acuerdo con los informes de EASA y de EUROCONTROL de los últimos diez años, los accidentes del tránsito aéreo se han reducido drásticamente, no obstante, los incidentes han tenido un auge significado. Especialmente, los incidentes debido a la separación entre aeronaves han sido calificados como una de las categorías de incidentes con mayor riesgo y prioridad por resolver.

Aproximando a esta dirección, este trabajo de investigación se ha enfocado en analizar los incidentes de pérdida de separación, junto con los informes publicados por CEANITA, con la intención de modelizar sus causas utilizando métodos estadísticos. A partir de ahí, con la ayuda de métodos matemáticos modernos, se realizan las predicciones que podrían identificar los posibles escenarios críticos de los incidentes o incluso los accidentes de colisión en el aire.

Adicionalmente, otros dos puntos de interés en desarrollo: i) se revisa y modifica la matriz de riesgo en evaluar la evolución de la criticidad de los incidentes; ii) se aplica la teoría de pirámide de Heinrich en proponer un modelo de predicción más sofisticado.

INTENTIONALLY LEFT BLANK

CONTENTS

1.	INTRODUCTION.....	1
1.1.	Introduction to Accident/Incident Investigation	2
1.2.	Motivation	10
1.3.	Objective and Scope.....	11
1.4.	Thesis Structure	12
2.	STATE OF THE ART	15
2.1.	Aviation Safety Review	16
2.2.	Predictive Model for Aviation Safety	23
3.	METHODOLOGY	27
3.1.	Process I – Incident Data Collection	29
3.2.	Process II – Incident Modelling	31
3.3.	Process III – Accident Prediction	33
4.	INCIDENT DATA COLLECTION	35
4.1.	Introduction.....	36
4.2.	Methodology of Incident Data Collection.....	37
4.2.1.	Incident Investigation Report or Occurrence Notification Analysis	38
4.2.2.	Incident Investigation Sequential Analysis	38
4.2.3.	Incident Investigation Database Creation	39
4.3.	Case Study: Loss of Separation Incident in Edmonton, Canada	41
4.3.1.	Overview from Incident Investigation Report	41
4.3.2.	Incident Analysis with ADREP Taxonomy Encoding.....	41
4.4.	Discussion	48
4.5.	Conclusion.....	51
5.	INCIDENT MODELLING	53
5.1.	Introduction.....	54
5.2.	Materials and Methodology.....	55
5.2.1.	Process of Analysis	57
5.2.2.	Modelling Process	59
5.3.	Case Study	63
5.3.1.	AIRPROX Occurrence Notification and Investigation.....	63
5.3.2.	Proposed BN Modelling.....	64
5.3.3.	BN Model Sensitivity Analysis	76
5.3.4.	BN Model Validation	80
5.4.	Analysis and Discussion	82
5.5.	Conclusion.....	86
6.	ACCIDENT PREDICTION	89

6.1.	Introduction.....	90
6.2.	Methodology of Accident Prediction.....	91
6.2.1.	Causal-effect analysis for serious & major LOS incidents.....	92
6.2.2.	Development and validation of the BN model.....	92
6.2.3.	Information theory application.....	92
6.2.4.	Development and evaluation of predictive scenarios.....	93
6.3.	Case study: assessment of four years of LOS in Spanish Airspace.....	95
6.3.1.	Case study phase 1: Causal-effect analysis for serious & major LOS incidents (steps 1 thru 4).....	95
6.3.2.	Case study phase 2: Development and validation of the BN model (step 5).....	96
6.3.3.	Case study phase 3: Information theory application (step 6 thru 9).....	111
6.4.	Conclusion.....	119
7.	HUNTING BLACK SWAN.....	121
7.1.	Introduction.....	122
7.2.	Objectives.....	124
7.3.	Briefing of Risk Matrix and Target Level of Safety.....	126
7.4.	Methodology of Development.....	131
7.4.1.	Definition of mathematical parameters.....	133
7.4.2.	Confusion matrix in terms of probability (step 1).....	136
7.4.3.	Separation of subsets and their characterizations of uncertainties (step 2).....	138
7.4.4.	True Positive Rate analysis (step 3a).....	139
7.4.5.	False Positive Rate analysis (step 3b).....	141
7.4.6.	Risk analysis in function of TPR and FPR values (step 4).....	145
7.4.7.	Proposal of the adapted risk assessment matrix (step 5).....	147
7.4.8.	Predictive risk assessment (step 5).....	149
7.4.9.	Algorithm.....	151
7.5.	Analysis and Discussion.....	152
7.6.	Conclusion.....	157
8.	HEINRICH PYRAMID THEORY.....	158
8.1.	Introduction.....	159
8.2.	Objectives.....	161
8.3.	Methodology.....	162
8.4.	Results of Application.....	165
8.5.	ANN Model Proposal from the Analysis Result.....	174
8.6.	Conclusion.....	176
8.6.1.	Benefits of the application.....	176
8.6.2.	Limitations of the application.....	177
8.6.3.	Future work.....	177

9. CONCLUSION	178
9.1. Final Discussion	179
9.2. Roadmap for Future Work	182
LIST OF PUBLICATIONS.....	184
BIBLIOGRAPHY.....	186
APPENDIX A – ATM INCIDENT DATABASE NORMALIZATION.....	198
A.1 INTRODUCTION	199
A.2 DEPENDENCY DIAGRAM	200
A.3 FIRST NORMAL FORM (1NF).....	202
A.4 SECOND NORMAL FORM (2NF).....	203
A.5 THIRD NORMAL FORM (3NF)	204
A.6 BOYCE-CODD NORMAL FORM (BCNF)	205
A.7 NORMALIZATION AND DATABASE DESIGN	206
APPENDIX B – ADREP TAXONOMY CODE	208
B.1 TAXONOMY CODES OF EVENTS	209
B.2 TAXONOMY CODES OF DESCRIPTIVE FACTORS	210

INTENTIONALLY LEFT BLANK

LIST OF FIGURES

FIGURE 1-1 – PASSENGER-KILOMETRES PERFORMED TOTAL SCHEDULED TRAFFIC, 2009-2018 (SOURCE: ICAO ANNUAL REPORT 2018)	2
FIGURE 1-2 – IATA FORECAST PREDICTION AIR TRAVELLERS IN 2037 (SOURCE: IATA / TE)	2
FIGURE 1-3 – NUMBER OF FATALITIES INVOLVING LARGE AEROPLANE PASSENGER AND CARGO OPERATIONS WORLDWIDE, 1970-2018 (EASA ANNUAL SAFETY REVIEW 2019)	4
FIGURE 1-4 – ACCIDENTS AND SERIOUS INCIDENTS OF COMMERCIAL AIR TRANSPORT PER YEAR 2008-2018 (EASA ANNUAL SAFETY REVIEW 2019).....	4
FIGURE 1-5 – NUMBER OF ACCIDENTS AND SERIOUS INCIDENTS OF COMMERCIAL AIR TRANSPORT BY FLIGHT PHASE, 2008-2018 (EASA ANNUAL SAFETY REVIEW 2019).....	5
FIGURE 1-6 – COMPARISON OF NUMBER OF OCCURRENCES AND AGGREGATED ERCS SCORE PER SAFETY ISSUE (EASA ANNUAL SAFETY REVIEW 2019).....	5
FIGURE 1-7 – COMPARISON OF NUMBER OF OCCURRENCES AND AGGREGATED ERCS SCORE PER KEY RISK AREA, 2014-2018 (EASA ANNUAL SAFETY REVIEW 2019).....	6
FIGURE 2-1 – THREE AGES OF SAFETY (HALE AND HOVDEN, 1998)	16
FIGURE 2-2 – CHARACTERISATION OF SAFETY MODELS AND MAIN ACCIDENT INVESTIGATION METHODS	21
FIGURE 2-3 – SAFETY MODEL BASED ON MATHEMATICAL METHODS	24
FIGURE 3-1 – GLOBAL METHODOLOGY	27
FIGURE 4-1 – PROPOSED METHODOLOGY FOR INCIDENT DATA COLLECTION.....	37
FIGURE 4-2 – QUESTIONS AND LEVELS TO BE ANALYSED IN THE BREAKDOWN OF AN OCCURRENCE	40
FIGURE 4-3 – EDMONTON INCIDENT ANALYSIS BASED ON FISHBONE SEQUENTIAL DIAGRAM.....	46
FIGURE 4-4 – FISHBONE SEQUENTIAL DIAGRAM WITH ADREP TAXONOMY ENCODING	47
FIGURE 4-5 – BAYESIAN NETWORK (BN) MODEL FOR EDMONTON INCIDENT INVESTIGATION.....	50
FIGURE 5-1 – BN MODELLING METHODOLOGY DIAGRAM.....	55
FIGURE 5-2 – LOS OCCURRENCE FRAMEWORK.....	58
FIGURE 5-3 – SPANISH INVESTIGATED INCIDENTS DURING FOUR CONSECUTIVE YEARS	64
FIGURE 5-4 – BN MODEL FOR SERIOUS LOS INCIDENTS IN CIVIL/COMMERCIAL AVIATION.....	72
FIGURE 5-5 – GENIE OUTPUT OF EVENTS AND DFs DURING FIRST THREE YEARS	73
FIGURE 5-6 – AFFECTED DFs LIKELIHOOD ESTIMATION WHEN EVENTS WITH PRESENT = 100%	74
FIGURE 5-7 – AFFECTED EVENTS LIKELIHOOD ESTIMATION WHEN EVENTS WITH PRESENT = 100%.....	75
FIGURE 5-8 – SENSITIVITY ANALYSIS WITH DFs RELATED TO A/C OR FLIGHT CREW AS TARGETS	77
FIGURE 5-9 – SENSITIVITY ANALYSIS WITH DFs RELATED TO ATM AS TARGETS	78

FIGURE 5-10 – SENSITIVITY ANALYSIS WITH DFS RELATED TO A/C OR FLIGHT CREW AND ATM AS TARGETS	79
FIGURE 5-11 – EVENT PROBABILITIES AND Nº OF ASSOCIATED DFS	82
FIGURE 6-1 – METHODOLOGY FOR ACCIDENT PREDICTION.....	92
FIGURE 6-2 – ROC CURVE FOR A BINARY CLASSIFIER.....	94
FIGURE 6-3 – SPANISH INVESTIGATED INCIDENTS OF SEVERITY A & B DURING FOUR CONSECUTIVE YEARS	96
FIGURE 6-4 – BN MODEL FOR LOS SERIOUS & MAJOR INCIDENTS IN COMMERCIAL AVIATION.....	107
FIGURE 6-5 – GENIE OUTPUT OF EVENTS AND DFS DURING FOUR CONSECUTIVE YEARS	108
FIGURE 6-6 – RESULTS OF THE SENSITIVITY ANALYSIS WITH COMMON DFS BETWEEN A/C AND ATM AS TARGET	109
FIGURE 6-7 – RESULTS OF THE SENSITIVITY ANALYSIS WITH DFS CORRESPONDING TO A/C AND ATM AS TARGET	110
FIGURE 6-8 – MUTUAL INFORMATION FOR EACH DF IN ALL EVENTS OF SERIOUS & MAJOR LOS.....	112
FIGURE 6-9 – ROC CURVE USING DFS OF SEVERITY A AS PRECURSOR DATA IN THE PREDICTION OF LOS	117
FIGURE 6-10 – ROC CURVE USING DFS OF SEVERITY B AS PRECURSOR DATA IN THE PREDICTION OF LOS	117
FIGURE 7-1 – RISK MATRIX FOR SAFETY OCCURRENCES (SOURCE: ICAO SAFETY MANAGEMENT MANUAL [39])	126
FIGURE 7-2 – TOLERABILITY OF SAFETY RISK (SOURCE: ICAO SAFETY MANAGEMENT MANUAL [39])	128
FIGURE 7-3 – METHODOLOGY OF RISK ANALYSIS BASED ON STATISTICAL CLASSIFICATION AND NEW RISK MATRIX PROPOSAL	131
FIGURE 7-4 – RELATIONSHIP BETWEEN SETS OF VARIABLES	136
FIGURE 7-5 – TPR-VS-TP/FN.....	139
FIGURE 7-6 – PROBABILITY AREA OF CAUSING INCIDENTS BASED ON TPR VALUES	140
FIGURE 7-7 – PROBABILITY AREA OF PRESENTING FACTORS IN NON-INCIDENT OPERATIONS BASED ON FPR VALUES	143
FIGURE 7-8 – SCENARIO OF LOSS OF SEPARATION DUE TO A WRONG MANOEUVRE BY OPERATIONAL CUSTOM	144
FIGURE 7-9 – GLOBAL VIEW OF TPR AND FPR ANALYSES	145
FIGURE 7-10 – RISK PATH	150
FIGURE 8-1 – METHODOLOGY OF CONVOLUTION OPERATOR APPLICATION TO HEINRICH PYRAMID THEORY IN DETECTING COMMON CAUSES BETWEEN INCIDENT SEVERITIES.	163
FIGURE 8-2 – HEINRICH’S PYRAMID BAYESIAN NETWORK (BN) MODEL FOR LOSS OF SEPARATION (LOS) SERIOUS AND MAJOR INCIDENTS IN COMMERCIAL AVIATION...	166
FIGURE 8-3 – DESCRIPTIVE FACTORS (DFS) WITH $I_{A \cap B} = 0$	169
FIGURE 8-4 – BOUNDARY CONDITIONS OF THE CASE STUDY.....	170
FIGURE 8-5 – DFS WITH $10^{-10} < I < 10^{-3}$ ($I \rightarrow 0$)	171

FIGURE 8-6 – DFS WITH $I > 10^{-3}$	172
FIGURE 8-7 – CONTRIBUTION PATH OF CAUSES TO INCIDENTS	173
FIGURE 8-8 – CONVOLUTIONAL NEURONAL NETWORK.....	175
FIGURE APPENDIX A-1 – ORIGINAL TABLE OF ATM INCIDENT REPORTS	200
FIGURE APPENDIX A-2 – CLEANED TABLE OF ATM INCIDENT REPORTS.....	201
FIGURE APPENDIX A-3 – DEPENDENCY DIAGRAM	201
FIGURE APPENDIX A-4 – INCIDENT_ID TABLE DESIGN VIEW.....	202
FIGURE APPENDIX A-5 – DATABASE RELATIONSHIP IN ACCESS	206

LIST OF TABLES

TABLE 2-1 – ATM ACCIDENT ANALYSIS MODELS	19
TABLE 2-2 – STRENGTHS AND WEAKNESSES OF SAFETY MODELS	20
TABLE 4-1 – EDMONTON INCIDENT EVENTS AND FACTORS IDENTIFICATION WITH ACCIDENT/INCIDENT DATA REPORTING (ADREP) TAXONOMY.....	45
TABLE 5-1 – AIR TRAFFIC OPERATIONS IN SPAIN FOUR CONSECUTIVE YEARS	63
TABLE 5-2 – SEVERITY A INCIDENTS IN THE LAST YEAR.....	66
TABLE 5-3 – AFFECTED Dfs LIKELIHOOD ESTIMATION WHEN EVENTS WITH PRESENT = 100%	67
TABLE 5-4 – AFFECTED EVENTS LIKELIHOOD ESTIMATION WHEN Dfs WITH PRESENT=100%.....	68
TABLE 5-5 – CPT OF EVENTS AND DESCRIPTIVE FACTORS UNDER SCENARIO OF LOS IN CIVIL/COMMERCIAL AVIATION.....	71
TABLE 5-6 – BN MODEL VALIDATION OUTPUT FROM GENIE 2.0.....	81
TABLE 5-7 – Dfs WITH MAJOR CONTRIBUTION WHEN ASSOCIATED EVENT PRESENT = 100%.....	83
TABLE 5-8 – THE REDUCTION OF EVENT LIKELIHOODS WITH BARRIERS ACTIVATED.....	83
TABLE 6-1 – CPT OF EVENTS AND DESCRIPTIVE FACTORS UNDER SCENARIO OF LOS IN COMMERCIAL AVIATION – SEVERITY A.....	100
TABLE 6-2 – CPT OF EVENTS AND DESCRIPTIVE FACTORS UNDER SCENARIO OF LOS IN COMMERCIAL AVIATION – SEVERITY B.....	106
TABLE 6-3 – EVALUATION OF PREDICTIVE SCENARIOS – SEVERITY A	114
TABLE 6-4 – EVALUATION OF PREDICTIVE SCENARIOS – SEVERITY B	116
TABLE 7-1 – SEVERITY OF THE EFFECTS ACCORDING TO THE CLASSIFICATION OF FAILURE CONDITIONS (SOURCE: EASA CS-25 [101])	127
TABLE 7-2 – ALLOWABLE PROBABILITY ASSOCIATED WITH CLASSIFICATION OF FAILURE CONDITIONS (SOURCE: EASA CS-25 [101])	129
TABLE 7-3 – RELATIONSHIP BETWEEN SEVERITY CLASSIFICATION AND RISK CLASSIFICATION FOR ATM SPECIFIC OCCURRENCES (SOURCE: ESARR 4 RISK ASSESSMENT AND MITIGATION IN ATM [105])	129
TABLE 7-4 – CONFUSION MATRIX IN TERMS OF FREQUENCY	137
TABLE 7-5 – EQUIVALENCE OF FREQUENCY OF OCCURRENCES BETWEEN FAILURES AND FACTORS	147
TABLE 7-6 – REDUCED RISK ASSESSMENT MATRIX	148
TABLE 7-7 – INCIDENT STATUS DURING FOUR CONSECUTIVE YEARS	152
TABLE 7-8 – RISK ASSESSMENT PRIORI AND POSTERIORI OF POTENTIAL SCENARIOS	155
TABLE 8-1 – MUTUAL INFORMATION MATRIX FOR TWO PROXIMATE CATEGORIES OF INCIDENTS	164
TABLE 8-2 – MUTUAL INFORMATION MATRIX FOR INCIDENTS OF SEVERITY A AND B	167
TABLE 8-3 – ASSOCIATED Dfs OF SEVERITY B WITH $I = 0$	168
TABLE 8-4 – ASSOCIATED Dfs OF SEVERITY A WITH $I = 0$	169
TABLE 8-5 – ASSOCIATED Dfs OF SEVERITY A AND B WITH $I \rightarrow 0$	170

TABLE 8-6 – ASSOCIATED DFS OF SEVERITY A AND B WITH $I > 0$	172
TABLE 8-7 – ASSOCIATED EVENTS IN SEVERITY A AND B WHEN DF 24010102 IN PRESENT STATE.....	173
TABLE APPENDIX B-1 – ASSOCIATED EVENTS IN SEVERITY A AND B WHEN DF 24010102 IN PRESENT STATE	209
TABLE APPENDIX B-2 – ASSOCIATED EVENTS IN SEVERITY A AND B WHEN DF 24010102 IN PRESENT STATE	211

INTENTIONALLY LEFT BLANK

ABBREVIATIONS

ABBREVIATION	DEFINITION
A/C	Aircraft
ABM	Agent-Based Modelling
ACC	Area Control Centre
ACC	Accuracy
ADREP	Accident / Incident Data Reporting
AEB	Accident Evolution and Barrier Analysis
AIRPROX	Aircraft Proximity
AMC	Acceptable Means of Compliance
AMJ	Advisory Material Joint
ANS	Air Navigation Service
ANSP	Air Navigation Service Provider
ASM	Air Space Management
ATC	Air Traffic Control
ATCO	Air Traffic Control Officer
ATFM	Air Traffic Flow Management
ATHEANA	A Technique for Human Error Analysis
ATM	Air Traffic Management
ATS	Air Traffic Service
ATSB	Australian Transport Safety Bureau
AWY	Airway
BN	Bayesian Network
CAA	Civil Aviation Authority
CAT	Commercial Air Transport
CATS	Causal model for Air Transport Safety
CEANITA	Comisión de Estudio y Análisis de Notificaciones de Incidentes de Tránsito Aéreo
CPT	Conditional Probabilistic Table
CREAM	Cognitive Reliability and Error Analysis Method
CRM	Collision Risk Model
CS	Certification Specification
DAG	Directed Acyclic Graph
DF	Descriptive Factor
EASA	European Aviation Safety Agency
ECCAIRS	European Co-ordination Centre for Accident and Incident Reporting System

ABBREVIATION	DEFINITION
ECFA/C	Event and Conditional Factors Analysis / Charting
EF	Explanatory Factor
EKEBN	Expert-based Knowledge Engineering of Bayesian Network
EPIS	Estimated Posterior Importance Sampling
ERCS	European Risk Classification Scheme
ESARR	European Safety Regulatory Requirement
ETA	Event Tree Analysis
EU	European Union
FDM	Flight Data Monitoring
FH	Flight Hour
FMEA	Failure Mode and Effect Analysis
FMECA	Failure Mode, Effects and Criticality Analysis
FN	False Negatives
FP	False Positives
FPR	False Positive Rate
FRAM	Functional Resonance Analysis Method
FT	Fault Tree
FTA	Fault Tree Analysis
GA	General Aviation
HAZOP	Hazard and operability
HERA	Human Error in ATM
HPES	Human Performance Enhancement System
HRA	Human Reliability Analysis
IATA	International Air Transport Association
ICAO	International Civil Aviation Organization
IFR	Instrument Flight Rules
IRP	Integrated Risk Picture
IT	Information Theory
KLD	Kullback-Leibler divergence
LOO	Leave One Out
LOS	Loss of Separation
MAC	Mid-Air Collision
MIL	Military
MLP	Multilayer Perceptrons
MORT	Management Oversight and Risk Tree
MTO	Man-Technology-Organisation

ABBREVIATION	DEFINITION
MTOW	Maximum Take-Off Weight
NextGen	Next Generation Air Transportation System
NM	Nautical Mile
OH	Operative Hour
Op	Operation
PRA	Probabilistic Risk Assessment
PT	Probability Table
QRH	Quick Reference Handbook
RAT	Risk Analysis Tool
RCA	Root Cause Analysis
ROC	Receiver Operating Characteristic
SCM	Swiss Chess Method
SESAR	Single European Sky ATM Research
SHELL	Software, Hardware, Environment & Liveware to Liveware
SMI	Separation Minima Infringement
SMM	Safety Management Manual
SOAM	Safety Occurrence Analysis Methodology
SOL	Safety through Organizational Learning
SQL	Structured Query Language
SRM	Safety Risk Management
STAMP	System-Theoretic Accident Model and Processes
STCA	Short Term Conflict Alert
STEP	Space, Time, Entity and Process
TCAS	Traffic alert and Collision Avoidance System
TEM	Threat and Error Management
THERP	Technique for Human Error Rate Prediction
TLS	Target Level of Safety
TMA	Terminal Manoeuvring Area
TN	True Negatives
TP	True Positives
TPR	True Positive Rate
UK	United Kingdom
WH	Working Hour
WP	Waypoint

INTENTIONALLY LEFT BLANK

Chapter 1.

1. INTRODUCTION

'On Friday of last week an extremely regrettable and most unusual accident marred the running of the London Continental Air Service, which has hitherto been remarkably free from serious disasters. It is an accident, also, all the more unfortunate in that it involved the recently inaugurated Daimler Hire Service. A Goliath belonging to Grands Express—F-GEAD—piloted by M. Mire and carrying a mechanic and three passengers had left Le Bourget at 12.6 p.m. for Croydon. The weather was very misty and visibility bad, and when flying over Thieuloy, near Grandvilliers, at a height of only a few hundred feet, a D.H. 18, from Croydon—G-EAWO—of the Daimler Service, piloted by R. E. Duke and carrying a boy steward and mails, suddenly loomed out of the mist. Before either pilot could turn, the machines collided, and then crashed to earth in flames. The D.H. 18, it is stated, had its wing and tail broken off by the impact and fell immediately, whilst the Goliath swooped to earth a little further off. Assistance was at once rushed to the wrecked machines, but with the exception of the boy steward — Hesterman—who was terribly injured, all were found to be dead. The boy was taken immediately to the village, but died from his injuries some time later.'

— 'London-Paris machines collide', Flight 215. 13 April 1922. Retrieved 29 March 2007

The news published in *Flight International* magazine on 13th April 1922 marked the first registered Mid-Air Collision (MAC) [1], occurred on 7th April 1922, between two commercial aircraft with civilian casualties in the aviation history [2] [3]. Since then, operational safety in the aviation industry has had a long way of continuous developments and improvements.

1.1. Introduction to Accident/Incident Investigation

Demand for commercial air transport has increased globally over the last decade according to the summary of International Civil Aviation Organization (ICAO) [4] as indicated in Figure 1-1, and the growth is forecast to reach 8.2 billion air travellers by 2023 as predicted by IATA [5] in Figure 1-2. Consequently, the aviation industry has also had to develop and improve technologically in order to respond to this demand. However, this technological improvement has already made and should continue to take care of all aspects related to operational safety such that any new implementation would not mean a decrease in the safety levels already accomplished.

Figure 1-1 – Passenger-Kilometres Performed Total Scheduled Traffic, 2009-2018 (Source: ICAO Annual Report 2018)

Figure 1-2 – IATA Forecast Prediction Air Travellers in 2037 (Source: IATA / TE)

Growing demand in air transport means, in terms of air traffic management (ATM), increasing the number of aircraft in a determinate airspace per unit of time. This fact brings the consequence of decreasing the distance between aircraft and, at the same time, increasing the probability of incidents, even accidents.

Severe safety incidents and accidents are a matter of concern, although the European Union Aviation Safety Agency (EASA) [6], and other aviation safety organisations, declare that air transport is currently acknowledged as the safest global mode of transport. As shown in Figure 1-3, the evolution of large aeroplane passenger and cargo, aircraft certificated MTOW over 2250kg, through the 1970s resulted in fatal accidents has a tendency to reduce over the past twenty years. In the last decade, as detailed in Figure 1-4 in spite of a significant decrease in accidents, the number of serious incidents has been increasing all the time.

The average numbers of serious incidents and accidents during this last decade presents a similar distribution pattern to the numbers for 2018 in different phases of flight. From Figure 1-5, four principal phases are identified with more incidents and accidents occurred: en-route, approach, take-off and landing. Most of incidents and accidents occurred during en-route phase of flight, commonly referred as loss of separation (LOS) or separation minima infringement (SMI) and MAC respectively, are considered critical due to the failure related to airborne separation.

As the ERCS indicator provided in Figure 1-6, airborne separation causes the most MAC accidents and LOS incidents during the years 2014-2018. ERCS, European common risk classification scheme, is an indicator that classifies the risk of all occurrences reported to the European Authorities and is capable to discriminate between occurrences of higher and lower associated risk. It has been developed by EASA in collaboration with an expert group composed by relevant European Risk Experts, and its application is mandated by the Regulation (EU) 376/2014. For example, one near-mid-air collision would be classified as a serious incident, whilst a collision with substantial damages between handling vehicle and an aircraft would be classified as accident. However, in terms of risk, this serious incident would

INTRODUCTION

be higher risk than the accident. Then, the combination of probability and severity would significantly differ.

Additionally, EUROCONTROL has recorded 827 and 930 incidents of severity A+B during 2017 and 2018 respectively [7]. Among them, 287 incidents in 2017 and 341 incidents in 2018 correspond to LOS incidents due to non-compliance with separation minima between airborns. These occurrences have been defined by EASA as the second key risk area for aviation in Europe [6], just behind runway incursion as shown in Figure 1-7.

Figure 1-3 – Number of Fatalities Involving Large Aeroplane Passenger and Cargo Operations Worldwide, 1970-2018 (EASA Annual Safety Review 2019)

Figure 1-4 – Accidents and Serious Incidents of Commercial Air Transport Per Year 2008-2018 (EASA Annual Safety Review 2019)

Figure 1-5 – Number of Accidents and Serious Incidents of Commercial Air Transport by Flight Phase, 2008-2018 (EASA Annual Safety Review 2019)

Figure 1-6 – Comparison of Number of Occurrences and Aggregated ERCS Score Per Safety Issue (EASA Annual Safety Review 2019)

Figure 1-7 – Comparison of Number of Occurrences and Aggregated ERCS Score Per Key Risk Area, 2014-2018 (EASA Annual Safety Review 2019)

One air traffic accident is an undesirable operational result from diverse dramatic perspectives such as negative public confidence in aviation transport, economic costs and, the most important, human lives lost. Then, every air traffic accident should be investigated, and this is required by ICAO through Annex 13 [8] for all participants in this worldwide organization of aviation.

Notwithstanding, accidents like MAC are rare, so relevant data are scarce. Because of the low-frequency, high-consequence nature, MAC are not well represented by conventional statistical models. In the absence of sufficient accident direct data, precursor-based probabilistic risk analysis methods are considered a promising and efficient tool for this purpose [9]. The widely-accepted definition of an accident precursor is an event with no catastrophic or severe consequences but that could have developed into an accident if additional safety barriers had failed [10] [11] [12] [13] [14].

The significance of precursors in the analysis of major accidents has been explored in several safety-critical industrial sectors, such as space shuttle explosions [13], nuclear power accidents [15] [16]; gas and oil accidents [17]; transport accidents [18] [19]; etc.

Since major accidents are frequently preceded by a number of accident precursors, there is a huge opportunity to reduce the risk of MAC by improving insight into MAC's main precursors, known as LOS or '*loss of separation*' events, as LOS events occur more often in airspace without necessarily having adverse or catastrophic consequences.

A LOS between in-flight aircraft happens when the safety separation minima prescribed in controlled airspace by air traffic service's (ATS) authorities, according to ICAO standards, are not observed. Different degrees of severity are established depending on the seriousness of the consequences of the LOS. The severity of a LOS is defined by the risk of collision (risk of ending up in a MAC), according to the minimum achieved separation between the involved aircraft and their rate of closure. EUROCONTROL [20] has established five levels of severity that range from the most severe, A, '*Serious incident*'—i.e., a high risk of collision—to the less severe E, '*No safety effect*'; with intermediate levels being B, '*Major incident*'; C, '*Significant incident*'; and D, '*Not determined*'.

Recent increases in reported losses of the required minimum in-flight separation between aircraft produced sufficient alarm to persuade all interested parties to urge occurrence reporting and share the outcomes of the resultant studies in order to improve mitigations. According to the Airborne Conflict Safety Forum, there are approximately 150 losses of separation per million flights in European-controlled airspace [21]. Considering that on average each flight receives 15 air traffic controller instructions while flying en-route, this signifies one loss of separation per 100,000 air traffic controller instructions.

Although the numbers for LOS are small compared to traffic volume, they are still regarded as critical safety indicators. Because of the severity of its potential consequences, LOS is considered the main proxy and a precursor to a potential MAC, and consequently, the analysis of contributing factors and the multi-dependent relationship between causal factors

of LOS incidents is encouraged as an effective way to mitigate LOS instances and prevent MAC.

EASA has recently produced an industry best practice document identifying relevant LOS precursors (contributing factors and the multi-dependent relationship between causal factors) to be monitored through Flight Data Monitoring (FDM) programs [22]. However, this work only focuses on those precursors that can be monitored from the data recorded on board. The investigation of LOS occurrences and their precursors from an Air Traffic Control (ATC) point of view is not so ingrained, in part due to the inherent complexity of such incidents and in part due to the scarcity of information available for their detailed analysis. To compensate for this partial approach, this research is constructed from the official reports of investigations of LOS occurrences produced by the official States Incident Investigation Authorities.

The reporting, investigation, and analysis of these occurrences are of prime importance to address this risk. The current status of these three processes, i.e. the i) reporting, ii) investigation, and iii) modelling of LOS, is summarised as follows.

- I. Reporting of LOSs between aircraft provides basic information to identify safety-related trends and to foresee emergent safety risk [23]. ICAO Annex 13 [8] requires states to establish accident- and incident-reporting systems to investigate causes of aviation accidents and to issue recommendations to prevent similar accidents from occurring again in the future. ICAO has also developed Accident/Incident Data Reporting (ADREP) taxonomy for collecting, sharing, and analysing safety information. The European Union, through the European Regulation (EU) No 376/2014 [24], has made the reporting, analyses and follow-up of safety incidents in civil aviation mandatory. Moreover, the European Safety Authorities have developed a repository, the European Co-ordination Centre for Accident and Incident Reporting System (ECCAIRS), to facilitate the collection and exchange of information about aviation accidents and incidents [24] [25]. According to this policy, the causes of accidents and incidents should be identified and codified in the ECCAIRS common database following the ADREP taxonomy [26].

- II. The data collected from occurrences investigation should be subsequently exploited to derive safety recommendations and preventive actions to control and reduce the risk of future accidents. In a proactive safety context [27], information from a wide range of incidents could improve risk assessment models and support the safety decision-making process [28].
- III. During the past three decades, researchers have developed substantial models to explain the occurrence of aircraft LOSs. The pioneering works of Reason [29], Rasmussen [30], and of other researchers have left a deep impression upon the comprehension of organisational decision-making in safety-critical systems. An accident or a serious incident can be interpreted as the result of a situation in which latent failures combine adversely with local events and active failures caused by human operators to brake the '*defences*' or cause '*a failure of the barriers*' in the aviation system [31]. Combining the principals of Reason approach with the SHELL model for gathering factual data, EUROCONTROL has developed a Systemic Occurrence Analysis Methodology (SOAM), which is a bespoke model for the analysis of ATM occurrences, which is useful in addressing LOSs between aircraft [32].

1.2. Motivation

Viewing EASA reports over the last ten years (2008-2018), the accident rate has presented a downward trend due to the great work done among all participants within this aviation industry. However, the number of serious incidents has witnessed a significant increase, especially the incidents occurring in the en-route phase because of the SMI between aircraft are more severe. Therefore, we need first to understand what has occurred (incident model) and how we can prevent it (predictive analysis).

Currently, EUROCONTROL has been successful in using the observed causal relationships to develop a predictive model based on the Fail Tree model, known as Integrated Risk Picture (IRP), with the goal of detecting potential conflicts between aircraft [19]. Nevertheless, this model presents limitations in its basic levels when trying to incorporate failures caused by human errors. This type of failure by human error has been considered as primordial importance in aligning the ideology of Safety-I and its current evolution to Safety-II [33]. Consequently, we attempt to improve this IRP weakness with the support of Bayesian Networks (BNs).

From a point of view of the current panorama of the air traffic management system, many new technologies have been developed over the last decade under the environment of SESAR and NextGen, with the target of improving air traffic capacity, increasing the efficiency in operations, thus also reducing the emission. However, we can doubt on how these technologies are going to provide support in the reduction of incidents or even accidents, and how they would behave in avoiding operational failures. Before being able to assess the technologies, it is necessary to know how the failures are connected. For this reason, as an additional point of interest, this thesis aims to develop an incident model capable to assess the efficiency of new technologies verifying how the likelihood of each failure is reduced.

1.3. Objective and Scope

The usage of identified causes in incidents as precursors for accident prediction has become a very popular safety technique [11] [15] [9]. However, in the aviation industry, this technique has not been widely applied for various reasons such as the difficulty of collecting actual data and scarce sources for prediction; especially the difficulty of analysis is increased when dealing with operational failures with human errors in the present.

This present thesis aims to propose a novel method of analysing air traffic incidents with an approach to predicting accidents. The causes and operational failures in air traffic incidents can be analysed with approved safety models like SOAM. Taking account that all operations in current air traffic management systems are regulated, hence, the taxonomy database created by ICAO is incorporated, on the one hand, in coding causes and failures as precursors to accidents, on the other hand, in generating an exhaustive database of ATM incidents that is capable of identifying correlations between them. The identification of correlations will not only provide great support in building our predictive model later, but also has highlighted the importance of the connection between human errors and operational failures within the model.

In the aviation industry like other industries with a higher level of safety, accidents, as well as incidents rarely occur. This means that the techniques applied to big data analysis are not suitable for predicting air traffic accidents due to their small data. Consequently, it reduces our choice of predictive models. Notwithstanding, in the incident database the relationship between causes and failures is identified, which is an essential requirement to construct a Bayesian Network model with predictive characteristics.

Additionally, the BN model can provide an in-depth analysis to identify which causes are most influential within air traffic incidents and, in the role of precursors, present risks of causing accidents. In this way, we can also create potential scenarios for accidents with these present cases.

1.4. Thesis Structure

The present thesis dissertation aims to provide a new perspective of ATM incident modelling based on expert-build and frequency data-driven, which can be used to determine the principal precursors to accident and, therefore, assess the potential scenarios for future prevention as the target.

After the introduction in **chapter 1**, the rest of this dissertation is organised as follows:

Chapter 2 summarises the current state of the art and introduces the motivation of this research work. In this section, an overview of relevant safety models developed into different engineering sectors for incident or accident analysis is summarised and discussed, as well as the need for developing this research work.

Chapter 3 introduces the methodology employed in this research work. The description of the methodology in this section is divided into the next two parts:

1. ATM incident modelling (Process I & II). All influential factors and their associated events are extracted from incident reports and stored as mathematical parameters in one database, hence that their correlations are established for the incident model construction.
2. ATM accident precursor and potential scenario determination (Process III). The incident model provides statistical information related to the relevant factors and events involved in all analysed incidents. The most correlated factors and events in the incident model are interpreted as the precursors to accidents, which are able to create different predictive scenarios.

Chapter 4 presents the incident data collection and, consequently, the database construction.

The principal safety model including its adaptation applied to the analysis of air traffic incident reports is detailed, as well as the main steps on incident data extraction from incident reports and the subsequent construction of incident database are described in this chapter.

Chapter 5 presents the construction of ATM incident model. With a created database as stating point, one Bayesian Network for ATM incident modelling is constructed. In this chapter, all data of LOS incidents of severity A that occurred during four consecutive years between all types of flight (commercial, military and general aviation) are considered for BN model creation and validation.

Chapter 6 presents the analysis of accident prediction. In this chapter, the incident data is extended to consider LOS incidents of severity B, meanwhile, the type of flight involved in incidents is only focused on commercial aircraft. The most influential causes are identified using the BN model constructed based on severity A and B incident data. Then, the potential scenarios to accidents are created and assessed by applying the information theory (IT).

Chapter 7 presents the analysis of risk assessment derived from the previous analysis of accident prediction. In this chapter, one innovative risk assessment matrix is proposed for fast detection of the most influential factors in incidents that can make a relevant contribution to causing accidents.

Chapter 8 presents the analysis of common factors correlated between two proximate categories of incidents, as well as the verification of Heinrich's Pyramid Theory for incidents occurred into ATM systems. In this chapter, considering the previous analysis and the result of accident prediction, convolution operator is applied to mutual information estimation in detecting common factors, especially measuring their connections between two proximate incident levels. As a result, a Bayesian-driven neuronal network model is proposed.

Finally, the main conclusion and different directions for future works are presented in **chapter 9**.

INTENTIONALLY LEFT BLANK

Chapter 2.

2. STATE OF THE ART

In this dissertation, in order to construct a model for predicting air traffic accidents, the first step is to know how safety science has evolved throughout its history, as well as the reasons why accidents occur. For this purpose, section 2.1 reviews both the previous work carried out by the previous researchers who constitute the state of the art of modelling accidents, as well as the history of safety science in general to understand its different stages of development.

In this manner, it is managed to better understand what happens in the aviation industry.

After this review of the general history of safety, the safety model to be developed is identified and discussed in section 2.2 on the search for the mathematical model, as a tool, which should satisfy the essential requirements demanded by the safety model in order to carry out its construction.

2.1. Aviation Safety Review

Historically speaking, from the industrial revolution in 1769 to present, safety science can be identified with five ages during its development. Hale and Hovden [34] have described the first three ages of safety as illustrated in Figure 2-1, which named '*the age of technology*', '*the age of human factors*', and '*the age of safety management*'. Glendon et. al. [35] have postulated an alternative view considering that the development in each period has been built on the previous, and the previous ways of thinking remain available to be reflected on multiple or complex perspectives. This process of development is referred to as the fourth age or '*the integration age*'. Notwithstanding the suggested integration age, Borys et. al. [36] have introduced the concept of fifth age or '*the adaptive age*' of safety, which holds closely adaptive cultures and resilience engineering, thus embracing human variability as an asset challenges the comfort of management.

Figure 2-1 – Three ages of safety (Hale and Hovden, 1998)

Safety in the aeronautic industry is younger than in other traditional industrial sectors. In Figure 2-1 we can observe that its rapid development began after the middle of '*the age of technology*'. In this age several useful methods like Fault Tree, Failure Mode and Effects Analyses (FMEA), Hazard and Operability Analysis (HAZOP) and Probabilistic Risk Assessment (PRA) were created and are still applying systematically to detect hazards and

risks for reliability engineering. However, due to the boom of new technologies and the presence of human participation into positions of higher-level decision making with automation, the methods developed during '*the age of technology*' and their associated models for safety have been limited only for failures of physical components and for relatively simple systems [37]. Hence, the idea of '*human error*' was introduced into the new development of safety model and the technical risk analysis was separated between reactive safety and proactive safety. Although human factors presented great participation in complex systems that require frequent human-machine interactions, accidents like the Space Shuttle '*Challenger*' Disaster highlighted that the organisational failure was more critical than simple human error, and as consequences, the focus was projected on development and research of safety management systems. The pioneering works of Reason [29], Rasmussen [30], and of other researchers have left a deep impression on the comprehension of organisational decision-making in safety-critical systems. They considered that the human contribution to system disasters should distinguish two kinds of error: active error and latent error [38]. The active error, whose effects are arisen immediately, is involved with the performance of the '*front-line*' operators of a complex system. Whereas the latent error is generated by agents whose activities are removed from the direct control interface in time and space, and its adverse consequence may lie dormant within the system until it combines with other factors to breach defences of the system. The acts due to these kinds of error are defined as an active failure and latent condition, whose combination can aggravate the consequences of unsafe acts on defences, barriers and safeguards of the system, then trace the accident trajectory.

In aviation, the practices of reactive approaches and proactive methods still find themselves in the evolution from compliance-based safety toward performance-based safety [39] [40], or in other words, a shift from '*the age of human factors*' to '*the age of safety management*'. Even a set of paradigms sustains this shift:

- The evolution from Safety-I to Safety-II, described by Hollnagel [33]. Safety-I is concerned with infrequent events that can go wrong in a stable environment,

meanwhile, Safety-II is concerned with the more frequent events that used to go right in a non-stable environment. Safety-I and Safety-II differ in their ontology, but they present two complementary views of safety.

- New safety methods and models capable to learn from both Safety-I and Safety-II including stories of failures and success, and to represent not only the complexity of modern socio-technical systems but also the dynamics of the interactions between humans, technical systems and the environment. Among the most influenced models can be categorised as epidemiological models [41] [42] [43]; agent-based models (ABM) [44]; systemic accident models in which System-Theoretic Accident Model and Processes (STAMP) [45] and the Functional Resonance Analysis Method (FRAM) [46] are more distinguished in usage; etc.
- The reporting and evaluation of serious and less serious safety events. The full working process for relevant civil aviation occurrences can be identified with steps as reporting, storing, exchanging, analysis and dissemination. The aim of this process consists of the identification of appropriate emergent safety events and risks, and corresponding safety actions to take. Therefore, the effective, proactive, and deep exploitation of safety data is key for safety improvement in the complex air transportation system.

Despite the construction of Safety-III devised by Hollnagel as the integration of Safety-I and Safety-II, thus aligning with '*the integration age*' toward '*the adaptive age*', the lack of interconnection between the three paradigms is still concerned today. On the one hand, classic safety methods, such as sequential models, are discarded in the analysis of complex scenarios due to their limitations, and missing the potential from a multi-method point of view in the safety management context. On the other hand, modern safety methods are complex, intensely laborious and cannot be applied straightforwardly to information and data analysis for later aviation safety database creation. Moreover, the potential of this kind of database neither for detecting nor for predicting emergent safety events have been fully exploited yet, then the extraction of the maximum amount of safety data has not fully succeeded, although a solid notifying culture related to safety events and occurrences has been performed in

aviation. For this task, modern methods should be set aside for classic methods, such as sequential and epistemological models that still play a positive role in the systematization of the occurrence database.

According to the aforementioned model categorization, Table 2-1 provides a summary of the most well-known safety models used for air traffic accident investigation and accepted by EUROCONTROL [47].

Classification	Models	Characteristics
Sequential	ATHEANA, Domino, CATS, ECFA/C, Fishbone, FMEA/FMECA, FTA/ETA, HAZOP, MORT, RCA, Root cause, STEP, THERP	<ul style="list-style-type: none"> - Consider sequences or series of events. - Might add barriers to prevent events evolving into accidents. - Might use conditions that permit the event. - Might consider logical gates to combine events into other events.
Epidemiological	AcciMap, AEB, CREAM, HRA, MTO, SCM, SHELL, SOAM, SOL, TEM, TRIPOD	<ul style="list-style-type: none"> - Considers not only events but a layer of latent conditions into the model. - Events are explained as consequences of actors' actions. - Actors are conditioned by their organizations.
Systemic	FRAM, STAMP	<ul style="list-style-type: none"> - Aimed to capture the strong hidden links and influences between the components of the system. - Each method has its own ontologies and paradigm to model the environment. - STAMP is a system-theoretical control cycle model that integrates sensors, control, controllers, actuators, and conceptual models to control the process. - FRAM model the system and its context in terms of functions, function characteristics (input, resources it needs, outputs, controls and real-time behaviour), and interactions between the functions. Outputs of the functions are explained by stochastic resonance leading to undesired effects.

Table 2-1 – ATM accident analysis models

In the literature of safety modelling, different comparisons have been analysed, i.e. Underwood [48] used ATSB, AcciMap and STAMP models for train derailment analysis; Smith [49] applied FRAM and FTA for understanding industrial safety; Arnold [50] presented a qualitative analysis between SOAM and STAMP for ATM occurrence investigation; etc.

With the transcendental analyses by these researchers, especially by Hollnagel [51], Table 2-2 presents the main strengths and weaknesses of each model.

Classification	Strengths	Weaknesses
Sequential	<ul style="list-style-type: none"> - Mature and consolidated methods. - Easy to understand. Good for communication and convince management. Narratives are available for sequential models to identify entities and relations. - Might represent a causal network of states and events leading up to an incident or accident, but without considering feedback loops. - They consider failures, incidental factors, deviations from a norm, unsafe acts, and to a certain extent, the social environment. 	<ul style="list-style-type: none"> - Socio-technical context is not taken into account. - Only clear and simpler improvements can be identified. - Limitation on describing multi-state component behaviours.
Epidemiological	<ul style="list-style-type: none"> - Take socio-technical context into consideration. - Focus on elements that cannot be analysed by sequential models such as company culture, safety procedures, legislation, etc. 	<ul style="list-style-type: none"> - They require more time and effort because of the bigger investigation scope. - They are more complicated because of the difficulties of capturing the context in a comprehensive narrative. - As they are focus on organizational and managerial shortcomings are sometimes perceived as treating by managers.
Systemic	<ul style="list-style-type: none"> - They acknowledge the tight coupling of individual functions and constituents of the system. 	<ul style="list-style-type: none"> - Disparate descriptions of these methods. - Small correspondence between different methods, such as FRAM and STAMP. - Difficult to create an overarching narrative for the accidents, then moderate reliability. - Difficult to apply and longer application time. - Extra effort might not be justified in many cases by the benefits of analysis, particularly when the consequences of incidents are relatively minor. - Less effective graphical communication.

Table 2-2 – Strengths and weaknesses of safety models

Perrow [52] proposed two dimensions composed of interactiveness and coupling to characterise accidents. Systems classified based on interactiveness can be identified as complex and linear. The principal features of a complex system, in contrast to a linear system, are listed as follows:

- Information sources are indirect or inferential.
- Isolation of failed components presents limitations.
- Some processes of transformation are difficult to understand.

- Control parameters present potential interactions.
- Personnel specializations limit awareness of interdependencies.

System classified based on coupling this parameter can be identified as tight and loose. Coupling in the system means that subsystems and components are connected or shown dependency between them in a functional sense. Then, the principal features of a tight system, in contrast to a loose system, can be summarised as follows:

- Sequences are invariant.
- Redundancies are part of the design.
- There is only one method to reach the goal.
- Tightly coupled systems are difficult to control, one event occurred in one part of the system can be transmitted to other parts quickly.

Figure 2-2 – Characterisation of safety models and main accident investigation methods

Hollnagel proposed new terminology using manageability instead of interactiveness by practical reasons [51]. The manageability measures the degree of management or control of

the system, where the extremes are tractable and intractable systems. One system or process is considered as tractable, if the principles of functioning are well known, its descriptions are simple with sufficient details, and the most important, if the system does not change while it is being described. Conversely, one system or process is intractable when the principals of functioning are partly known or even unknown, its descriptions are elaborated with excess details, and the system may change before the description is completed. As a summary, Figure 2-2 presents the classification of safety models based on these criteria of Perrow and Hollnagel.

2.2. Predictive Model for Aviation Safety

According to the aforementioned classification and characterisation of safety models, particularly based on criteria of Perrow, corresponding mathematical models can be associated with as follows:

- Linear and deterministic. Sequential models are representative of this modelling. Analysis of an accident shows that cause A leads to effect B in a specific situation, while A may be a composite event combining numerous causes [53].
- Non-linear and deterministic. Epidemiological and more complex socio-technical models present this characteristic in modelling. From fallible decision to accident, these models are deterministic, but no longer linear. The non-linear interactions between components in a complex system are those of unfamiliar, unexpected and unplanned sequences, either not visible or not immediately comprehensible [52].
- Non-linear and non-deterministic. In systemic models, an accident occurs when several causal effects enter into resonance in a specific time and space [54]. The relationships between these causes are inherently probabilistic (non-deterministic) and are probabilistically influenced (non-linear) by higher-order factors [55].

Then, a new version of characterisation regarding mathematical model is presented in Figure 2-3, with linearity and uncertainty as two dimensions.

Figure 2-3 – Safety model based on mathematical methods

An accident occurring within the ATM system, which Perrow and Hollnagel considered as a tightly coupled and non-tractable, presents characteristics of an organizational accident. Essentially, information sources in the ATM system are inferential and events will spread quickly, from one part of the system to other parts, due to the high interaction between components. To be able to capture these characteristics, one non-linear and non-deterministic network approach should be required for aviation accident modelling.

Although the accident presents high-consequence in nature, is low-frequency in occurrence. Data on operational failures are very limited extracting from actual occurrence investigations or official notifications. For this reason, risk analysis methods based on precursors extracted from incident scenarios are considered a promising tool [56] to estimate accidents or near accidents [57]. Then, accident prediction could not be raised as a problem that is solved by applying big data techniques, such as Artificial Neuronal Network or Monte Carlo Method.

In recent years, Bayesian Network has been proposed to implement uncertain knowledge representation and reasoning. Bayesian Network presents several advantages of data analysis [58] in the following:

- i. Generally, Bayesian Network is used to model causal relationships, so is capable to predict the consequences of intervention.
- ii. Especially, it is useful in modelling uncertainty in a domain.
- iii. Due to causal and probabilistic semantics of the model, Bayesian Network is ideal to represent the combination of prior knowledge and data.
- iv. Moreover, it easily handles situations where some data entries are missing.

INTENTIONALLY LEFT BLANK

Chapter 3.

3. METHODOLOGY

The main target of this thesis has been focused on developing an ATM safety model capable to forecast accidents, including incidents, in order to take preventive actions before they get too late. Toward this goal, during the development of this research project, we have proposed a series of methodologies for source data collection, model generation and posterior predictive analysis. As illustrated in Figure 3-1, the global methodology leading this thesis is divided into three principal processes with ten main steps.

Figure 3-1 – Global methodology

The process I consists of four steps related to incident data collecting, in which all influential factors and adverse events contributing to determinate incidents are extracted from reports and stored in a database as mathematical parameters. As the result of this process, with

selected category of incidents, type of involved aircraft, kind of operations, etc. as boundary conditions for our incident analysis, the correlation between factors and events can be detected to provide support in the decision-making of model selection.

In the process II, the whole process of incident modelling based on Bayes theorem is detailed, as well as its validation. Due to the limited size of the database and the multi-dependent relationship presented by source data, we have considered that the Bayesian Network approach should be suitable to service the research purpose.

Lastly, in process III, applying the entropy used in Information Theory to all parameters located in BN model, the most relevant precursors to accidents can be detected, thus the creation and assessment of potential scenarios that contribute to accidents.

Additionally, by reason of not causing the misinterpreting, causes and factors are referred to the same terms during mathematical model construction and its consequent analyses in next chapters, as well as events and failures.

3.1. Process I – Incident Data Collection

The notification and evaluation of occurrences present prime importance in safety analysis, as well as investigation and reporting after the fact. Furthermore, they provide essential information for guiding safety-related trends and arising emergency safety risk. As the starting point of this process (step 1), all ATM incident investigation reports published by state investigation office are considered as input and classified according to three main categories derived from the ESARR 2 [59]: type of flight, incident severity and incident category. The selection based on these criteria allows the filter of incident reports with similar characteristics, consequently, facilitating the detection of common patterns.

Basically, one incident report can be divided into three blocks: i) incident scenario data: information provided by operational communication, data of radar trace, weather condition and place where the incident occurred, aircraft information, etc.; ii) the testimonies of involved agents, i.e. pilots and air traffic controllers; iii) conclusions and recommendations provided by state investigation office. The factual data contained in each block should be gathered following a series of criteria, as well as the link between thereof should be established. Therefore, as step 2, SOAM approach is used to accomplish these requirements in order to identify adverse events and influential factors with criteria defined in EAM 2 / GUI 8 [60]. In the SOAM approach, all factual data are examined and collected by applying two tests. ‘*TEST 1*’ is focused on the identification of factual data in incident reports and ‘*TEST 2*’ on the classification of these results into four categories: *Absent or Failed Barrier*, *Human Involvement*, *Contextual Conditions* and *Organisational Factors*. However, as an approach derived from the Reason model [48] [60], SOAM presents two important gaps in advanced computational analysis.

- ‘*TEST 2*’ presents a detailed analysis of factual data being difficult to encode and store in an incident database. During our research work, the four categories defined in ‘*TEST 2*’ were adopted to answer a set of questions, which break down an occurrence into a sequence of events. This breakdown highlights the causal link between events

characterised by descriptive factors and explanatory factors. In summary, events are considered as effects or stages that set the incident in motion; meanwhile, both factors are interpreted as causes of failure.

- The factual data collection method used in SOAM lacks in processing the sequence of the incident scenarios, the temporal relationship between data and chronological vision of the incident. Under the premise that the traceability and the sequence should be kept, analysis and organization of temporal dependency relationship between factual data require the application of one sequential diagram. Fishbone or Ishikawa diagram is very frequently used in the detection of failure causes for industrial accident investigation; nevertheless, we have proposed the extension of its usefulness toward dynamic analysis, which aims to incident scenarios reconstruction.

Therefore, all factual data within the four categories defined in SOAM approach and, transformed into events and factors by a set of questions later can be reorganized as incident variables and connected by a temporal line. Such events and factors are codified using ADREP taxonomy with standard description and corresponding reference number. This process of codification is identified as step 3.

Additionally, during the process of transformation in step 2 and the codification in step 3, we considered the opinion of several experts with a comparison study proceeded to determine the taxonomy with more accuracy.

As a result of previous steps, incident reports are definitely transformed from texts to simple cases formed by events and factors, also called precursors, which should be stored in one database as mathematical parameters (step 4). In the practical application, the database has been created by Microsoft Excel and Access SQL for further information management.

3.2. Process II – Incident Modelling

The aim of this process is focused on development and validation of an ATM incident model using the database created in the process I. Such model should present predictive feature to determine the adverse events and associated influential factors in future ATM incidents. Observing properties and structure of the data, we have considered that Bayesian Network approach acquires rather capacity to capture this specific feature in a complex system as air traffic management system.

The BN is a probabilistic direct graphic approach that created to emphasises three aspects in a causal or temporal relationship: i) the subjective nature of the input information; ii) the reliance on the conditioning of Bayes as the basis for updating information; ii) the distinction between causal and evidential modes of reasoning. The structure of a BN model consists of a Direct Acyclic Graph (DAG) in which variables are represented by nodes and connected through arcs. The arrow is drawn from each node of the parent set toward the child node and the strength of each arc contents the information related to the conditional probability between two nodes.

Technics as expert-built and frequency data-driven were applied to the proposed model construction. Moreover, to elicit expert knowledge, a process referred to Expert-based Knowledge Engineering of Bayesian Network (EKEBN) was employed. The whole process is divided into three main steps: i) structure building, ii) uncertainty quantification, and iii) model validation. The first two steps i) and ii) are identified as step 5 of our proposed methodology in Figure 3-1. They correspond to model construction using expert knowledge and real data. Lastly, step iii) takes expert verification in an iterative process into account, in which experts assessed iteratively the models to eliminate inconsistencies and discrepancies. This validation by experts gathering the numerical validation defines the full process of validation as step 6. BN model development in step 5 and numerical validation in step 6 are completed through a commercial software called GeNIe developed by BayesFusion, LLC. As numerical

validation, we have used the validation option offered by GeNIe based on Leave One Out (LOO) method, an extreme case of K-fold cross-validation method.

3.3. Process III – Accident Prediction

An accident precursor is an event without catastrophic or severe consequences but that could have developed into an accident if additional safety barriers had failed. ATM accidents and ATM incidents share common causes in the form of initialling adverse events and influential factors. The occurrence of an ATM incident makes information included in its causes conditional on the occurrence of a final accident.

In step 7, this conditional relationship can be quantified using the concept of mutual information. This concept is intricately linked to the concept of entropy of a random variable, the basis in Information Theory to quantify the expected amount of information held in a random variable. The entropy for an ATM incident can be explicit as $H(Z) = -\sum_{z \in Z} P(z) \cdot \log_2 P(z)$, where $P(Z)$ is a probability mass function for discrete random variables $Z = Z \{z_1, \dots, z_2\}$. When the probability of the causes Y is known, the entropy of Z should be rewritten as the conditional entropy $H(Z|Y) = -\sum_{z,y} P(z,y) \cdot \log_2 \frac{P(z,y)}{P(y)}$, and the mutual information $I(Z,Y)$ can be defined as $I(Z,Y) = H(Z) - H(Z|Y) = \sum_{z,y} P(z,y) \cdot \log_2 \frac{P(z,y)}{P(z) \cdot P(y)} = \sum_{z,y} P(y) \cdot P(z|y) \cdot \log_2 \frac{P(z|y)}{P(z)}$. Moreover, all conditional probabilities that are needed to continue with the calculation of mutual information are derived from BN model, which allows a quick and easy update of the mutual information when a new set of data become available. In practice, among the causes of an ATM incident, those are more informative when they fulfil criteria of having the highest mutual information and belonging to high incident severity, and they can be used to establish the probability of an ATM accident. Therefore, as step 8, different predictive scenarios are developed using these most informative causes individually or collectively.

In step 9, ROC curve is applied as a binary classifier to assess the performances of these predictive scenarios. A ROC curve presents the True Positive Rate (TPR) versus the False Positive Rate (FPR). The calculation of TPR and FPR values are formulated as $TPR = \frac{TP}{TP+FN}$

and $FPR = \frac{FP}{FP+TN}$. Notably, one additional parameter Accuracy (ACC) is used to measure the accuracy of the classifier: $ACC = \frac{TP+TN}{TP+FP+TN+FN}$.

The terms True Positive (TP), False Positive (FP), True Negative (TN) and False Negative (FN) are four components of the confusion matrix. If the outcomes of one experiment can be labelled using binary classification: positive or negative, then all possible outcomes can be summarised as follows:

- TP: if the outcome from a prediction is positive and the actual value indicates the same;
- FP: if the outcome from a prediction is positive, but the actual values is negative;
- TN: conversely to TP, both the prediction outcome and the actual value are negative;
- FN: conversely to FP, if the prediction outcome is negative, whilst the actual value is positive.

Finally, step 10, the most effective predictive scenarios are identified from all potential scenarios just examining the values of TPR, FPR and ACC. Additionally, streams of causes that contribute to incidents have been detected. With this last result, a Bayesian-driven neuronal network model has been proposed to predict forward incidents.

Chapter 4.

4. INCIDENT DATA COLLECTION

In this chapter, we acknowledge limitations as well as strengths of the different types of methods and propose a different application for the more conventional sequential methods in a pre-processing phase, in combination with epistemological methods, such as SOAM, and the most complete and up-to-date aviation safety taxonomy – ADREP.

4.1. Introduction

This work proposed to reactivate the use of a sequential method, the fishbone or Ishikawa diagrams, in combination with an epistemological method, the Safety Occurrence Analysis Methodology which is an adaptation of the Reason model by EUROCONTROL, and with the most complete aviation safety taxonomy developed by ICAO, ADREP taxonomy.

This approach allows a new interaction between traditional and new safety methods. A triplet of more conventional and somehow simpler safety methods and tools are used to pre-process information in safety occurrences, paving the way for the further exploitation of safety occurrence databases with much more complex, rich, and powerful methods, such as symmetry analysis or systemic methods. Additionally, the outcome of this preliminary step will facilitate the link between modern methods, such as the FRAM and STAMP, which could be easily applied in the air traffic management context linked with the ADREP taxonomy and SOAM methodology. A loss of separation incident that occurred in the Edmonton area is used as a case study to illustrate this methodology, as well as the whole analysis process.

4.2. Methodology of Incident Data Collection

Figure 4-1 presents the proposed methodology with the main processes that prepare every incident investigation, from reporting to mathematical analysis.

Figure 4-1 – Proposed methodology for incident data collection

As a starting point, the principal causes that lead to ATM incidents have to be investigated. Then, an analysis of the notified occurrences and investigation reports should be required in the first phase. During this phase, factual data of each incident is collected, applying the SOAM approach. However, a chronological vision of incident scenarios is not reflected in this data collection. The sequence of incident scenarios is considered as an important path to understand how incidents develop from a safe condition to a dangerous situation, and what relationships can be established between the causes based on their temporal evolution; therefore, a sequential analysis with identified factual data should be necessary for a second phase.

In the last phase of this analysis process, regarding ADREP taxonomy, all factual data can be classified as events or factors, which are stored as mathematical parameters in an incident database for further analysis.

4.2.1. Incident Investigation Report or Occurrence Notification Analysis

Regarding Regulation (EU) No 376/2014 [24], all interested parties implicated in aviation safety, e.g., pilots, ATM / Air Navigation Service (ANS) staff, and manufacturers, are responsible for reporting occurrences to the competent authorities and, through this medium, make civil aviation safety achieve a high general level in the EU. At a global level, ICAO Annex 13 [8] requires contracting states to establish systems for the reporting of accidents and incidents, and to detect the causes and recommend improvements for real or potential shortcomings; furthermore, according to ICAO Annex 11 [61], it is the responsibility of the contracting states to investigate all air traffic incidents that take place in their airspaces. Once the investigations are concluded, every corresponding state investigation office has the responsibility to publish investigation reports as results. In this first step of this analysis process, ATM incident investigation reports are considered as input and the SOAM approach is used to locate the direct links between the conditions of the occurrence and the actions of the people involved [32], thus gathering factual data thereof. Based on the SOAM approach, in this second step, factual data for collection can be classified in four categories: '*Barrier Absent or Failed*', '*Human contribution*', '*Contextual Circumstance*', and '*Organizational Influence*'.

4.2.2. Incident Investigation Sequential Analysis

As References [60] and [32] noted, the SOAM approach was developed based on the Reason model [29]. Therefore, its factual data collection method loses in this processing the sequence of the incident or accident scenarios, the temporal relationship between data, and a chronological vision of the incident or accident. For reasons of keeping the traceability and the sequence, one sequential diagram should be used to analyse and organize the temporal dependency relationship between classified factual data (step 3).

In industrial sectors, a fishbone or Ishikawa diagram is commonly used as a tool for accident investigation analysis. Chang and Lin [62] illustrated how one fishbone diagram was developed to identify the principal causes of tank accidents and another was developed for their prevention. Meanwhile, researchers like Kunadharaju et. al. [63] only applied this diagram for identifying the principal components of fatalities during a work process. Nevertheless, the usefulness of this diagram can be extended toward dynamic analysis in order to reconstruct incident scenarios. Thus, all factual data within these four categories of the SOAM approach can be reorganized and linked with a temporal line.

4.2.3. Incident Investigation Database Creation

As well as factual data gathering, factual data storing presents the same importance for future incident or accident investigations. Two rules are followed in this phase of the methodology:

- **Encodability:** Each datum can be encoded with a reference number and a standard description.
- **Uniqueness:** Each datum only represents one event or factor. If a combination of more than one factor or event is detected for a factual datum, this data should be separated in individual ones to identify their factors or events.

Events and factors are identified by applying a set of questions proposed by Ferrante et. al. [64]. According to the conclusion of these researchers, an occurrence can be broken down using ADREP taxonomy into a sequence of events, and the same events are composed of descriptive factors and explanatory factors (step 4). This relationship between events and factors is represented in Figure 4-2. In the first level, the answer to the question '*What?*' corresponds to an event; in the second level, the answer to the question '*How?*' corresponds to Descriptive Factors (DFs), which identify the symptoms of each event; and in the last level, the question '*Why?*' corresponds to Explanatory Factors (EFs), which reflect the causes of the occurrence. The ICAO ADREP taxonomy [65] provides codification to these answers with reference numbers and standard descriptions (step 5). This information conversion aims to

store all data extracted from incident investigations in a database tool, like Microsoft Access SQL, for further information management (step 6).

Additionally, following the process performed in [64], for each event and factor, we considered the opinions of three experts, and the comparison study proceeded to determine the taxonomy with more accuracy.

Figure 4-2 – Questions and levels to be analysed in the breakdown of an occurrence

4.3. Case Study: Loss of Separation Incident in Edmonton, Canada

To illustrate the application of this methodology, one case study related to a loss of separation incident was chosen for analysis. This case occurred on 27 June 2002 near Edmonton (Canada) between CPB888 and CNS213 aircraft, in which we applied our procedure of analysis together with ADREP taxonomy usage. The case was investigated by the Canadian Government [66] and summarized as follows.

4.3.1. Overview from Incident Investigation Report

The occurrence, a loss of separation, took place in the afternoon on the 27th of June, 2002. Two airplanes were involved in the occurrence: A BA3112 operated by Corpac Canada Ltd., registered as C-GKGM with the call-sign CPB888; and an SA227DC operated by Alta Flights, registered as C-FDMR with the call-sign CNS213. The CPB888 was flying from Edmonton to Calgary under Instrument Flight Rules (IFRs) in an en-route phase of the flight, while the CNS213 was IFR en-route from Calgary to Edmonton. Due to bad weather conditions, both aircraft were diverted east of their original flight plan, and encountered each other, on opposite headings and FL160. Final separation between the traffic was 200 vertical feet and 1.3 NM, quite below the minimum separation prescribed for that airspace.

4.3.2. Incident Analysis with ADREP Taxonomy Encoding

The whole occurrence from the development of the first failure made to the end of this incident can be divided into four adverse events based on SOAM analysis and presented in a sequential diagram, as illustrated in Figure 4-3. Each adverse event was supported by several influential causes that were extracted from the incident report as follows:

1. Pilot of aircraft (A/C) CPB888 did not question an inadequate altitude.
 - a. Air traffic controllers in that sector were used to issuing altitudes inappropriate for directions.

- b. According to Canada Flight Supplement planning documentation, ATC may assign altitudes inappropriate for the direction of flight at any point along preferred routes between Edmonton and Calgary.
- 2. A/C CPB888 was instructed to fly at an inappropriate altitude for the direction of flight.
 - a. Controllers were used to vector aircraft operating at inappropriate altitudes.
- 3. Controller cleared A/C CNS213 to the same altitude that A/C CPB888 without adequately scanning the radar for traffic and possible conflicts.
 - a. All the ATC team at the sector (planning and executive controller as well as supervisor) were at the end of their shifts and they were possibly fatigued.
 - b. Traffic was high and complex at the moment of the operation in the sector.
 - c. Inadequate management of staff contributed to a high workload.
 - d. The bad weather added extra workload to the controller that had to negotiate avoidance deviations.
 - e. The area control centre (ACC) was not equipped with a ground-based conflict alert system.
- 4. None of the controllers in the sector detected the conflict between the two aircraft.
 - a. Aircraft was not traffic alert and collision avoidance system (TCAS)-equipped.
 - b. Conformance to altitude and strip marking standards was not regularly checked.
 - c. Canada flight supplement planning documentation allowed ATC to assign altitudes inappropriate for the direction of flight at any point along preferred routes between Edmonton and Calgary.
 - d. ATC was suffering fatigue and high workload.
 - e. Traffic was high and complex due to weather avoidance deviations.

All adverse events detected in this case study have corresponding events in ADREP taxonomy; such correspondence can be either one to one, or that one adverse event can be composed of different events defined in ADREP taxonomy, e.g., the adverse event from SOAM '2. A/C CPB888 was allowed to operate at an inappropriate altitude for the direction of flight' has been identified in one event of ADREP taxonomy 'Deviation from clearance—

assigned flight level' with encoding '2020517'; meanwhile, the adverse event '*1. Pilot of A/C CPB888 did not question an inadequate altitude*' is composed of two events of ADREP taxonomy '*Provision of flight information by the ANS related event*' and '*ANS clearance to wrong altitude*', with encoding '2020601' and '2020202'. Similar to all extracted influential causes from the incident report applying SOAM, they present correspondences with defined DFs as well as EFs in ADREP taxonomy. Based on the characteristics of the taxonomy that each taxon is independent of the others, the independency of every event, DF, or EF can be demonstrated. Through this simple sample, as a result, an incident report with SOAM analysis is transformed into mathematical parameters with codification, as presented in Table 4-1. Then, the sequential diagram presented in Figure 4-3 is transformed in Figure 4-4 with ADREP taxonomy encoding.

INCIDENT DATA COLLECTION

Adverse Event Identified in Report	Event	Influential Causes Identified in Report	Descriptive Factor (DF)	Explanatory Factor (EF)
Pilot of A/C CPB888 did not question an inadequate altitude.	t = t(1): <i>Provision of flight information by the ATS (Air Traffic Service) related event. (2020601)</i>	Bad practices of Pilots in receiving inadequate altitude in this sector for flight direction.	<i>Flight crew's control of the A/C altitude. (12240300)</i>	<i>Experience of route. (105010205)</i>
	t = t(2): <i>ANS clearance to wrong altitude. (2020202)</i>	Air traffic controllers in that sector used to issue altitudes inappropriate for directions. According to Canada Flight Supplement planning documentation, ATC may assign altitudes inappropriate for direction of flight at any point along preferred routes between Edmonton and Calgary	<i>ASM (Air Space Management) conditional route type. (24030202)</i>	
A/C CPB888 was instructed to fly at an inappropriate altitude for the direction of flight.	t = t(3): <i>Deviation from clearance—assigned flight level. (2020517)</i>	Controllers used to vector aircraft operating at inappropriate altitudes.	<i>ATC provision of a minimum safe FL (24010704)</i>	<i>ATS incorrect / inappropriate / inadequate. (201020100)</i>
		According to Canada Flight Supplement planning documentation, ATC may assign altitudes inappropriate for direction of flight at any point along preferred routes between Edmonton and Calgary	<i>ASM conditional route type. (24030202)</i>	
Controller cleared A/C CNS213 to the same altitude that A/CCPB888 without adequately scan radar for traffic and possible conflicts.	t = t(4): <i>Navigation track error. (2170400)</i>	All the ATC team at the sector (planning and executive controller as well as supervisor) were at the end of their shifts and they were possible fatigued.	<i>ATC monitoring of sector traffic load. (27030000)</i>	<i>Fatigue-other (102030900)</i>
		Traffic was high and complex at the moment of the operation in the sector.	<i>ASM updated capacity of an airspace. (24030300)</i>	<i>Work overload / task saturation. (204010100)</i>
		Inadequate management of staff contributed to a high workload	<i>ATC monitoring of sector traffic load. (27030000)</i>	<i>High workload due to staff / skills shortage. (204010200)</i>
		The bad weather added extra workload to the controller that had to negotiate avoidance deviations.	<i>Thunderstorm. (52031600)</i>	
		The ACC was not equipped with ground-based conflict alert system.	<i>ATC provision of information concerning en route weather phenomena that may affect the safety of A/C operations. (24010507)</i>	
			<i>ATC provision of a STCA (Short Term Conflict Alert) warning. (24010604)</i>	

Adverse Event Identified in Report	Event	Influential Causes Identified in Report	Descriptive Factor (DF)	Explanatory Factor (EF)
None of the controllers in the sector detected the conflict between the two aircraft.	t = t(5): <i>ANS conflict detection and resolution related event. (4010400)</i>	<p>Aircraft was not TCAS equipped.</p> <p>Conformance to altitude and strip marking standards was not regularly checked.</p> <p>Canada Flight Supplement planning documentation allowed ATC to assign altitudes inappropriate for direction of flight at any point along preferred routes between Edmonton and Calgary.</p> <p>ATC was suffering fatigue and high workload.</p> <p>Traffic was high and complex due to weather avoidance deviations.</p>	<p><i>Traffic alert and collision avoidance system / Airborne collision avoidance system (11344500)</i></p> <p><i>ATM of flight progress strip. (21040102)</i></p> <p><i>ASM conditional route type. (24030202)</i></p> <p><i>ATC monitoring of sector traffic load. (27030000)</i></p> <p><i>ASM updated capacity of an airspace. (24030300)</i></p> <p><i>ATC monitoring of sector traffic load. (27030000)</i></p> <p><i>Thunderstorm. (52031600)</i></p> <p><i>ATC provision of information concerning en route weather phenomena that may affect the safety of A/C operations. (24010507)</i></p>	<p><i>The interface between humans in relation to use of flight progress strips to communicate information. (501020200)</i></p> <p><i>Fatigue-other (102030900)</i></p> <p><i>Work overload / task saturation. (204010100)</i></p> <p><i>High workload due to staff / skills shortage. (204010200)</i></p>

Table 4-1 – Edmonton incident events and factors identification with accident/incident data reporting (ADREP) taxonomy

Figure 4-3 – Edmonton incident analysis based on fishbone sequential diagram

Figure 4-4 – Fishbone sequential diagram with ADREP taxonomy encoding

4.4. Discussion

This case study presents a loss of separation incident analysis using SOAM and ADREP taxonomies, as well as using a simple fishbone diagram for the incident scenario reconstruction keeping its sequential stages.

The SOAM analysis had led to the separation of an incident narrative report into four adverse events and a set of influential causes. Adverse events described the incident in terms of '*what has happened*'. The second layer of analyses allowed to decompose influential causes into descriptive factors that explained '*how the events took place*' and explanatory factors that explained '*why the events happened*'. The Ishikawa analysis captured the sequential relationship between these elements.

Combination of both methods allows a multidimensional dynamic description of safety occurrences. Every safety incident can be dissected into four dimensions: (1) Time; (2) why (explanatory factors) (3) how (descriptive factors) and (4) what (events). The four dimensions are excellent inputs for more complex safety methods such as FRAM or SATMP.

For example, in FRAM, the following six elements are defined for each FRAM function or hexagon. Time, a variable that takes into account temporal aspects. Output, the variable performs as results of the FRAM function. Input, which makes the FRAM function active; and three additional functions that regulate the outcome of the FRAM function, i.e., preconditions, controls, and resources. There is a direct correspondence between the dimensions of our approach and the variables in the FRAM model. Time is presented in both approaches; events correspond to the output of the FRAM function; explanatory factors are related to the inputs; meanwhile, descriptive factors can be identified as the preconditions, controls, and resources.

Additionally, the analyses applied in this section synthesized information embedded in safety occurrences into a taxonomy. It facilitates the application of statistical methods to obtain safety insight by applying modern data processing technologies. Forward analytic analysis, such as information theory or decision-making analysis like a Bayesian Network, can be

applied to understand the correlation between events and factors, as well as their contributions in serious incident scenarios.

Figure 4-5 presents a simple BN construction for the Edmonton incident. In this graphic model, the scenario can be identified as two sub-phases based on time:

- Preliminary conditions from time (1) to time (3). In this sub-phase, few adverse factors are presented in events and their multiple dependencies with events are limited. Then, the complexity of this sub-phase is reduced, and the unsafe situation is not critical.
- Critical conditions from time (4) to time (5). This sub-phase presents a complex interaction between factors and events. Notably, the absence of previous barriers to prevent the disclosure of these factors leads to this unsafe situation from not critical to critical LOS in the order of seconds.

In general, SOAM analysis is focused on organizational cause identification, then through this method, investigators have a clear and complete view of an incident scenario. However, analysis with this method results in loss of the sequential relationship between identified causes, and the incident scenario might be difficult to reconstruct. For this reason, ADREP taxonomy and a fishbone diagram contribute an additional value in order to keep the relationship between events chronologically, facilitate the incident scenario reconstruction, and provide an in-depth diagnostic of the impact of the order in which events occurred in loss of separation incidents. It should be noted that the connection between events or factors defined in ADREP taxonomy and causes detected during SOAM analysis do not always present a correspondence. As observed in this case study, one detected cause in SOAM analysis can be identified with more than one event in ADREP taxonomy.

Figure 4-5 – Bayesian Network (BN) model for Edmonton incident investigation

4.5. Conclusion

This work proposes to reactivate the use of fishbone or Ishikawa diagrams, a sequential method, in combination with the safety occurrence analysis methodology (SOAM), an adaptation of the Reason model (an epistemological method) by EUROCONTROL [60], and with the ADREP taxonomy, the most complete aviation safety taxonomy developed by ICAO. A loss of separation incident that occurred in the Edmonton area (Canada) is used as a case study to illustrate this methodology as well as the whole analysis process.

This proposal builds upon what can be considered three main paradigm shifts in aviation safety:

- The consideration of safety III, defined by Hollnagel [33], as a complementary combination between safety-I and safety-II concepts and approaches.
- New safety methods and models to learn from both success and failed safety stories, and to represent the complexity of modern socio-technical systems and the dynamics of the interactions between humans, technical systems, and the environment.
- The reporting and evaluation of serious and less serious safety events.

The proposed work is an initial step to mitigate the remaining lack of interconnection between the three elements above today. Despite Hollnagel's proposal of integration of traditional safety methods (Safety I) and modern safety approaches (Safety II), nowadays the three previous paradigms present weak interconnections. Classic safety methods are overlooked and rejected in favour of more multifaceted and fresh approaches, wasting the benefits of a multi-method perspective in the context of safety management. Meanwhile, the new safety methods are intricate, demand high levels of expertise, and cannot be straightforwardly applied to the analysis of the data and information compiled in aviation safety databases.

This work extensively discusses the strengths and weaknesses of the various types of safety investigation methods, in particular, the ones that are proposed to be combined (fishbone, a sequential method, and SOAM, an adaptation of the Reason epidemiological method). It also places our proposal in relation to other existing approaches, showing the benefits of a multi-

method approach for safety. This research is also contextualized as an instrument necessary for the application of symmetry analysis methods into aviation safety.

Our approach will allow a new interaction between traditional and new safety methods. The proposed triplet can be used to pre-process information in safety occurrences, paving the way for the further exploitation of safety occurrence databases with much more state-of-the-art methods such as FRAM or STAMP.

Through this methodology, we have also explored its advantage for possible computational applications in incident investigations. For this case study, a simple BN model was created to understand this specific incident scenario.

Chapter 5.

5. INCIDENT MODELLING

In this chapter, a new data-driven model for the analysis of severe commercial-aircraft LOS incidents will be proposed based on BN modelling. Data collected from severe-occurrence reports will be filtered into events and contributing factors following an *ad hoc* procedure of analysis. Both the events and the contributing factors will be considered as precursors of Mid-Air Collision accidents. The correlation between events and factors will be used to generate a quantitative cause-effect map that will become the structure of the BN model. The likelihood estimates will be derived from the number of reports investigated.

In the following paragraphs, the overall methodology will be explained, and a case study will be presented based on the analysis of LOS incidents which have occurred in the Spanish airspace during a period of four years.

5.1. Introduction

Roelen et. al. [67], in an attempt to accelerate the application of Reason's Swiss-cheese concept, developed CATS as a framework for multiple safety modelling methods [68]. It applies to ATM occurrences in all phases of flight and it is tailor-made for the study of LOSs between aircraft [69].

The EUROCONTROL IRP method is a step further in the process of modelling the risk of aircraft LOSs. This model consists of a combination of Fault Tree (FT) and influence diagrams. With this method, the concept of '*failure of a barrier*' is modelled in the aviation system through the relationship between technical failures and human errors in the FT diagrams. An additional influence model is developed in the IRP to show the effect of factors on safety management and the operational environment [19].

The trend of using the BN application in engineering has increased in the past few decades. This approach has been extensively applied in research studies on accident/incident investigation areas, such as environmental engineering [70], the natural gas industry [71], and the offshore industry [72]. In the aviation sector, BN models have been used to determine the causes of failure in avionic systems [73]; the performance of pilots [74], and in the aircraft diagnostic for maintenance [75]. Certain authors have also explored the application of the BN to the modelling of ATM safety occurrences. More specifically, Wilson & Huzurbazar [76] and Khakzad et. al. [77] have compared the fitness of FT and BN for modelling safety incidents. In spite of the fact that both models result in similar estimations for adverse occurrence likelihood, the BN is capable of updating prior beliefs by taking new information into account and generating more accurate probability estimations, whereas the FT is limited to handling only a set of multi-state variables, dependent failures, and uncertainties.

5.2. Materials and Methodology

Figure 5-1 summarises the methodology employed in the present research. In the first step, all incident reports should be classified according to three main categories derived from the ESARR 2 [59]: type of flight, incident severity, and incident category. In the second step, incident reports are selected, for forward analysis, following three criteria.

1. Selection by incident severity: Serious incident or Severity A;
2. Selection by incident category: LOS or SMI;
3. Selection by type of flight:
 - a) CAT-vs-CAT (CAT: commercial air transport)
 - b) CAT-vs-MIL (MIL: military), i.e. when a commercial aircraft is involved in an incident and the pilot executes the wrong procedure, which contributes to adverse events;
 - c) CAT-vs-GA (GA: general aviation), i.e. when a commercial aircraft is involved in an incident and its pilot executes the wrong procedure, which contributes to adverse events.

This selection allows the reduction and the grouping of incidents with similar characteristics, thus facilitating the detection of precursors.

Figure 5-1 – BN modelling methodology diagram

The next stage in the methodology is the '*process of analysis*', which encompasses three steps; in Figure 5-1, these are illustrated as Steps 3 through 5. In Step 3, the SOAM approach [32] is employed to analyse the content of the incident reports and to process factual data with criteria defined in the EAM 2/GUI 8 [60]. The analysis in Step 3 aims to identify adverse events and influential factors that took place in the incident. In Step 4, the adverse events and influential factors are extracted and encoded by applying the ADREP taxonomy [64]. The adverse events have a direct correspondence to the ADREP taxonomy [65] as events, whereas the influential factors extracted from reports are codified either as descriptive factors or as explanatory factors. Finally, in Step 5, all the information extracted from the incident reports, particularly the events and the influential factors, are registered in an incident database as mathematical parameters.

The last stage of the methodology is the '*process of modelling*'. In Step 6, events and influential factors are grouped in the database and are used for the building of a correlation map between events and influential factors. This correlation map is the basis to construct the causal model explaining the occurrence of LOS (Step 6). In this causal model, human or operational failures are interpreted as the failure of barriers in the operational procedures of ATM, following Reason's principles.

This causal model was implemented to a BN that has the potential to explain the current incidents and predict future ones. In the BN, a barrier corresponds to one influential factor or to an assembly of influential factors. In the BN, influential factors have two possible states, i.e. either '*present*' or '*absent*'. Then, the failure of a barrier is represented in the BN model by the '*present*' state of the corresponding influential factor. The effective performance of a barrier in the BN model is represented by the '*absent*' state of the corresponding influential factors. The efficiency of a barrier in preventing an incident is assessed through the induced likelihood variation in other events or influential factors.

In the following paragraphs, Steps 3 thru 6, which account for '*process of analysis*' and the '*process of modelling*', will be described in more detail.

5.2.1. Process of Analysis

At the beginning of the process of analysis, i.e. in Step 3, the SOAM approach is employed as a baseline to detect links between conditions of the occurrence and actions of people involved, eventually gathering factual data [32]. The first stage of the SOAM analysis for factual information storing is partially used in this phase of incident analysis. In the SOAM approach, two tests are presented to identify and collect factual data. With '*TEST 1*', all constructive information is extracted, which allows investigators to proceed to '*TEST 2*', which allows classification into the following four categories: Absent or Failed Barrier, Human involvement, Contextual Condition and Organisational Factor. In this research, '*TEST 1*' was valid for ATM incident-report analysis; meanwhile, the categories presented in '*TEST 2*' were substituted by a set of questions. These questions were proposed by Ferrante et. al. [64] in combination with the ADREP taxonomy (Step 4) to break down an occurrence into a sequence of events characterised by DFs and EFs. In a cause-effect relationship, events are interpreted as effects or stages that set the incident in motion. Both DFs and EFs are interpreted as causes of failure. In practice, the procedure of formulating questions is not followed as precisely as defined by Ferrante. As shown in Figure 4-2, the events are identified by responding to the question '*What type of event has happened?*', whereas DFs are the response to the question '*How did it happen?*' and EFs are the response to the question '*Why did it happen?*' The order of the questions is not strict. Questions related to DFs could be asked first, followed by questions related to events and EFs.

To examine the guidelines of occurrence investigation [60] and the basic structure of incident reporting, all events and factors relating to an occurrence should be analysed considering information from the following three areas:

- 1) Information provided by communication and radar trace.

This part of the report presents an occurrence in chronological order, including all communication which took place between involved agents and the registered radar data. According to this information, one occurrence framework is created and is then broken down into a sequence of layers as represented by the '*Swiss cheese*' in Figure

5-2. Each layer portrays an adverse event and prompts successive occurrence with LOS as the final target.

Figure 5-2 – LOS occurrence framework

2) Information provided by the registry of testimonies.

The abstract from the registry of testimonies collects the notifications of all involved agents (pilots and controllers) in ATM incidents. Information provided by these agents is valuable to complete the incident scenario and detect the circumstances under which the operational process was followed. The failures of the ATM operational process detected from the testimonies of involved agents arise commonly from two sources. One is the direct failure detection based on the standard ATM operational process, i.e. the controller does not detect the error of a readback from the pilot or the controller does not request the readback if the pilot does not provide it. The other is through the inconsistencies detected within the ATM operational process, as testified by involved agents and the same operation but recreated based on communication. The latter source enables the disclosure of mistakes related to human factor, i.e. incorrect ATC clearance given by the controller, the psychological action-mistake (faulty plan/intention) of the pilot, incorrect execution by the pilot not justified by the correct clearance given by controller, and the readback/hearback are verified by both pilot and controller.

In most cases, the influential causes or the contributing causes may be attributed to human factors and to the circumstances which are detected in every adverse event.

3) Information provided by investigation conclusion and authority recommendation.

The report conclusion and recommendation merely provide additional information to refine the identified influential causes.

Events and influential factors are encoded into the ADREP taxonomy; consequently, these can be stored systematically in one incident database for the next BN modelling (Step 5).

5.2.2. Modelling Process

The BN is a probabilistic graphic approach used to provide a mathematical method of reasoning for the analysis of serious incidents in the ATM system. The BN model consists of a directed acyclic graph, which reflects the relationship between a set of stochastic variables; these are identified as nodes and arcs, which represent probabilistic or functional influence linking two nodes [78]. The strength of the connections between both nodes is denoted by the conditional probability table (CPT) [79].

The proposed BN model has been constructed based on a combination of expert-built and frequency data-driven. To elicit expert knowledge, a process model referred to Expert-based Knowledge Engineering of Bayesian Network (EKEBN) was employed [80]. This process comprises three main steps: 1) structure building, 2) uncertainty quantification, and 3) model validation. The process is iterative until a complete BN is built and validated.

Structure building consists of the identification of variables, causal dependencies, and the states or values which correspond to each variable. Variables in the network correspond to the events and DFs extracted from incident reports by experts during the process of analysis (Steps 3 thru 5). Each report has been analysed by three experts at least. Following the process suggested by Ferrante et. al. in [64], each expert elicits the events and factors concurring in each incident.

Uncertainty quantification deals with the conditional probabilities which quantify the relationship between variables. This was initially realised by experts, nevertheless, it was later updated with the number of occurrences derived from the data.

The network structure and the initial estimation of experts for probability tables (PTs) and CPTs were elicited on paper. A variety of elicitation formats for the parameterisation of BNs is available in the literature. For this project, a group of six ATM and safety experts were carefully selected. The estimates of experts were treated equally, and no weighted averages were calculated. When discrepancies appeared during the development of the model, experts discussed the probability values until a group consensus was reached.

The BN structure was refined through an iterative process. The structure has been validated by two combined approaches. Experts were divided into two groups who assessed iteratively the models to detect inconsistencies and discrepancies. Additionally, the representativeness of the variables, causal dependencies, and possible states have been independently compared with the available literature. When no evidence supported the elicitation of the expert, the experts were asked to refine their appreciation. Additionally, consistency checks were performed to verify: i) if all variables had been clearly defined and they had unique meanings, ii) if all relevant variables had been included and all the states were exhaustive and exclusive.

The BN also represents a joint probabilistic distribution, $P(U)$, of variables $U = \{A_1, A_2, A_3, \dots, A_n\}$. Such distribution could be continuous or discrete, based on the conditional independence and chain rule [81] included in the network:

$$\text{Equation 1: } P(U) = \prod_{i=1}^n P(A_i | Pa(A_i))$$

where $Pa(A_i)$ is the parent set of A_i and $P(U)$ is the joint probabilistic distribution in the BN. The conditioned independence of each node and the dependency relationship between parent and child nodes are assumed. The explicit assumption $P(x_i | x_1 \dots x_{i-1}) = P(x_i | \text{parents}(X_i))$ was considered; it means that a DF is conditionally independent of the other DFs given an event (parent node). In addition, because of the characteristic of the taxonomy, each factor or event was defined as a taxon; consequently, these factors or events are independent of each other. For an ATM incident analysis, the BN applies the Bayes theorem to update the prior occurrence probability of events or factors (Step 6) depending on the

levels in consideration [77] by providing new inputs, referred to as evidence, E , to yield the posterior consequence probability via the following equation:

$$\text{Equation 2: } P(U|E) = \frac{P(U,E)}{P(E)} = \frac{P(U,E)}{\sum_U P(U,E)}$$

Equation 2 demonstrates either the probability prediction or the probability updating.

Prior probabilities are assumed to follow a multinomial distribution, with the parameter vector $\theta_1, \theta_2, \dots, \theta_n$ where n is the number of states of variable x and $\theta_k = P(x = x_k|p)$, for $1 \leq k \leq n$; the parameter θ possesses the Dirichlet distribution $\theta \sim D[\alpha_1, \alpha_2, \dots, \alpha_n]$, with $\alpha_i > 0$ ($i = 1, \dots, n$), and $\sum_{i=1}^n \theta_i = 1$. The parameters α_i represent counts of past cases that are stored as a summary of experience in the database produced in step 5.

In predictive analysis, conditional probabilities of $P(\text{event} | \text{factor})$ are calculated by specifying the occurrence probability of a particular event given the occurrence of a specific factor. In updating analysis, the $P(\text{factor} | \text{event})$ is evaluated by showing the occurrence of a particular factor given the occurrence of a specific event [82]. In fact, the values of $P(\text{factor} | \text{event})$ are calculated directly and collected in the CPT; on the contrary, the values of $P(\text{event} | \text{factor})$ can be estimated using the GeNIe software [83].

For belief updating in the BN, we used the '*clustering algorithm*', an inference algorithm offered as a default option by GeNIe. Clustering algorithms used to be fast for belief updating in BNs and were sufficient if the network would not be particularly large or complex. The algorithm was originally proposed by Spiegelhalter & Lauritzen [84] and was improved by researchers such as Jensen et. al. [85]. More specifically, for finite nodes, the k-means clustering was applied with the Dirichlet distribution. Additionally, regarding the default options, all the nodes in the network were defined as chance-general, all events and factors were defined either as '*present*' state or '*absent*' state, and the '*clustering and policy evaluation*' was activated in the options for the network configuration with a number of samples equal to 1000 and the Estimated Posterior Importance Sampling (EPIS) algorithm propagation length of 5.

The GeNIe software itself has a validation option, the aim of which is to capture the joint probability distribution over variables in all constructed BN models [86]. More specifically, this software allows the use of the LOO method, which is an extreme case of the K-fold cross-validation in which K is equal to the number of records (N) in the dataset. In LOO, the network is trained on $n-1$ records and is tested on the remaining one record. Then, the process is repeated n times.

5.3. Case Study

A period of four years of LOS incidents which occurred in Spanish airspace was considered to show the application of this methodology. For the sake of facilitating comprehension, this case study was structured in two phases:

- Phase 1: AIRPROX occurrence notification and investigation. It accounts for Steps 1 through 5 of the methodology. It covers incident classification, incident selection, and process of analysis.
- Phase 2: Proposed BN modelling. It details Step 6 of the methodology, including the development of the BN model, the BN model sensitivity analysis, and the BN model validation.

5.3.1. AIRPROX Occurrence Notification and Investigation

The air traffic operations for four consecutive years in Spanish airspace declared by ENAIRE, the Spanish Air Navigation Service Provider (ANSP), in its annual reports [87] are listed in Table 5-1.

YEAR	ARRIVALS/DEPARTURES	DOMESTIC	OVERFLIGHTS	TOTAL
Year 1	954255	541612	318046	1813913
Year 2	969271	456948	339450	1765669
Year 3	997063	475426	357039	1829528
Year 4	1012801	354807	362826	1730434
TOTAL	3933390	1828793	1377361	7139544

Table 5-1 – Air traffic operations in Spain four consecutive years

In Spain, air traffic incidents are reported to the Civil Aviation Authorities (CAA), which are responsible of analysing the incident and of publishing a report with the conclusions [88]. These reports include the factual data, the testimonies of the implicated individuals, the outcomes of the investigation, as well as the conclusions and the derived recommendations. Figure 5-3 presents two variables: the number of incidents and the categories of all reported incidents during a period of four consecutive years, $\{U\}$. In our research, the data collected from the ATM-reported incidents can be expressed as

$$\{U\} = \{U_{anal.}\} + \{U_{ass.}\}$$

where $\{U_{anal.}\}$ denotes the data collected from the first three years and $\{U_{ass.}\}$ denotes the data collected from the fourth year. Data from the first three years were used for the building of the BN model and the data from the fourth year were used for the validation of the BN.

Figure 5-3 – Spanish investigated incidents during four consecutive years

5.3.2. Proposed BN Modelling

The nodes of the BN correspond to the events and DFs obtained from the reports. Finally, EFs were not considered in this case study as nodes in the BN because owing to the limited information available in the incident reports which were analysed, it was not possible to properly extract them.

All nodes were defined as chance-general and had two single states: '*present*' or '*absent*'. Prior to the implementation of probabilities, nodes follow a multinomial distribution, representing counts of past cases during the four years period of analysis. The initial BN structure was based on expert knowledge. Belief updating from data and CPT were derived from data using a clustering algorithm.

As a default option, the '*clustering algorithm*' of GeNIe was used for belief updating in the Bayesian Network. A clustering algorithm is trained for a small and simple network, it is

considered as the fastest exact algorithm for belief updating in BN. This algorithm works in two phases in the junction tree: (1) compilation of a directed graph, and (2) probability updating.

The resulting network is illustrated in Figure 5-4. Events and factors shown in this BN model can be divided into five groups:

- Group 1 of events, parent nodes, related to A/C systems or the operations of the flight crew.
- Group 2 of events, parent nodes, related to ATM systems or operations.
- Group 3 of factors, children nodes, related to A/C systems or the operations of the flight crew.
- Group 4 of factors, children nodes, related to ATM systems or operations.
- Group 5 of factors, children nodes, related to the interaction of operations between the flight crew and ATM.

The connections of children nodes from Group 3 and 4 to corresponding parent nodes of Group 1 and 2 establish a unique dependency between events and factors. However, Group 5 presents complex connectivity with both event groups; this feature aims to affect the occurrence probability of all events involved in the LOS scenario, even if the occurrence probabilities of the factors of the same group are updated. The BN model identifies one weak dependency between both event groups through the same group of factors as a connection, i.e. in Figure 5-4, when the event related to '*Communication between pilot and air navigation service (ANS)*' occurs, the likelihood of implicated factors such as failure of '*Flight crew's air/ground/air communication*', '*Air traffic control (ATC) readback/hearback error*' not detected, or misunderstanding made during '*ATM civil sectors coordination of the same unit*' could be estimated. Consequently, the occurrence probability of events related to '*ANS operational communication*' could be updated.

The CPT of correlation between events and DFs is summarised in Table 5-5. The CPT has been calculated from the analysis of the dataset, $\{U_{anal.}\}$, corresponding to the incidents in the first three years. This table contents the likelihood of each factor and its conditional

probability to the associated event. As can be observed in Table 5-5, each event can be associated with one or more factors. Through this evidence, it may be inferred that behind an incorrect ATM operation, there are one or more causes establishing the fact that a mistaken decision was made. Applying GeNIe, the proposed BN model is constructed using the analysis dataset, $\{U_{anal.}\}$, and illustrated in Figure 5-5.

The assessment dataset, $\{U_{ass.}\}$, is listed in Table 5-2 and was used for the BN model application analysis. This analysis consisted of two parts:

- 1) Forward conditional probability approach: introducing events of the assessment dataset, $\{U_{ass.}|Event_i\}$, in the BN model to determine the DFs and comparing this result with real data $\{U_{ass.}|DF_i\}$;
- 2) Backward conditional probability approach: introducing DFs, $\{U_{ass.}|DF_i\}$, of assessment dataset in the BN model to determine events and comparing this result with real data $\{U_{ass.}|Event_i\}$.

Adverse Events (E)	Event Definition	Descriptive Factors (DF)	Descriptive Factor Definition
2020300	Communication between pilot and air navigation service related event	12252600	Flight crew's air/ground/air communication
		22080101	Air traffic management's internal coordination of civil sectors in the same unit
		24010102	Air traffic control use of readback / hearback error detection
4010400	Air Navigation Services conflict detection and resolution related event	22120100	Air traffic management's strategic planning for conflict detection
		22120200	Air traffic management's tactical execution of the conflict detection strategy
		23010300	Clearance procedure
4010600	Air Navigation Services handing over/taking over procedure	22080101	Air traffic management's internal coordination of civil sectors in the same unit

Table 5-2 – Severity A incidents in the last year

In general, the joint probability can be calculated applying the following equations derived from Equation 2, depending on the type of analysis required.

Equation 3 $P(DF_i) = \sum_j P(E_j) \times P(DF_i|E_j)$ for forward conditional probability

Equation 4 $P(E_i) = \sum_j P(DF_j) \times P(E_i|DF_j)$ for backward conditional probability

1) For the forward conditional probability approach, in Table 5-3, the following events were set to 1 (state=present) in the proposed BN model.

- ‘Communication between pilot and ANS’ (2020300)
- ‘ANS conflict detection and resolution’ (4010400)
- ‘ANS handing over/taking over procedure’ (4010600)

Then Equation 3 can be rewritten as $P(DF_i) = \sum_j P(E_j = 1) \times P(DF_i | E_j = 1)$, with criteria $P(DF = \text{Present}) > 0.25$ (first quartile) as principal candidates of the influential cause, which are identified in the BN model as listed in Table 5-3.

Descriptive Factors (DFs)	DFs Code	$P(DF) _{\text{estimated}}$
ATM civil sectors-unit	22080101	Present = 1.00
ATC readback / hearback error detection	24010102	Present = 0.69
Flight crew's air/ground/air communication	12252600	Present = 0.58
ATM clearance procedure	23010300	Present = 0.55
ATM tactical execution for conflict detection	22120200	Present = 0.40
ATM monitoring of aircraft	22060100	Present = 0.42
ATM strategic plan for conflict detection	22120100	Present = 0.34

Table 5-3 – Affected DFs Likelihood Estimation when Events with Present = 100%

When this estimated result of $P(DF)|_{\text{estimated}}$ is compared with the real collected data, $\{U_{ass.}|DF_i\}$, in Table 5-2, one additional DF, i.e. ‘ATM monitoring of aircraft’ (22060100), is detected. There are three assumptions regarding where this additional factor could be considered:

- i. This DF is not an influential factor in incidents. This assumption must be verified by examining all incident reports to check whether this factor was not omitted during analysis.
- ii. This DF was omitted during the incident analyses. This assumption could be verified by checking the results of all analyses to conclude whether this factor was missed and if so, to include this information in the database.
- iii. This DF was not detected during occurrence investigation, before the incident report was published. In this case, this factor could not be attested by witnesses nor could it be detected by investigators. This situation reveals the usefulness of the BN model,

which has been constructed based on historical incidents, in terms of supporting investigations.

In the present case, this additional DF does not contribute to incidents which belong to assessment dataset.

2) For the backward conditional probability approach, in Table 5-4, following DFs are set to 1 (state = present) in the proposed BN model:

- ‘*Flight crew’s air/ground/air communication*’ (12252600)
- ‘*ATM civil sectors-unit*’ (22080101)
- ‘*ATM strategic plan for conflict detection*’ (22120100)
- ‘*ATM tactical execution for conflict detection*’ (22120200)
- ‘*ATM clearance procedure*’ (23010300)
- ‘*ATC readback / hearback error detection*’ (24010102)

Equation 4 may be rewritten as $P(E_i) = \sum_j P(DF_j = 1) \times P(E_i | DF_j = 1)$, and the probabilities of affected events in the BN model are calculated and listed in Table 5-4.

Adverse Events (E)	Events Code	P(E) _{estimated}
ANS conflict detection and resolution	4010400	Present = 1.00
Communication between pilot and ANS	2020300	Present = 0.97
ANS handing over/taking over procedure	4010600	Present = 0.75
ANS operational communications	4010100	Present = 0.45
Air space capacity reduction	4070400	Present = 0.29

Table 5-4 – Affected Events Likelihood Estimation when DFs with Present=100%

Comparing this estimated result $P(E)|_{\text{estimated}}$ with the real data collected $\{U_{ass.} | Event_i\}$ in Table 5-2, two additional events ‘*ANS operational communications*’ (4010100) and ‘*Air space capacity reduction*’ (4070400) are detected. Based on the same analysis for additional DF, these two events are not presented in incidents that belong to assessment dataset.

Adverse Events (E)	Event Definition	P(E)	Descriptive Factors (DF)	Descriptive Factor Definition	P(DF)	P(DF E)
1230000	Communication systems related event	5.88E-02	12232800	Flight crew's operation of communication equipment	5.88E-02	1.00E+00
2020201	Air navigation service erroneous clearance	1.76E-01	22060100	Air traffic management's monitoring of aircraft	5.88E-02	3.33E-01
			24010703	Air traffic control provision of flight information	5.88E-02	3.33E-01
			25050000	Air traffic management service personnel operating procedures/instructions	1.18E-01	6.67E-01
2020202	Air navigation service clearance to wrong altitude	1.18E-01	22120100	Air traffic management's strategic planning for conflict detection	5.88E-02	5.00E-01
			24010704	Air traffic control provision of a minimum safe flight level/altitude/height/sector altitude	5.88E-02	5.00E-01
2020300	Communication between pilot and air navigation service related event	5.29E-01	12232800	Flight crew's operation of communication equipment	5.88E-02	1.11E-01
			12251800	Flight crew's radiotelephony phraseology	5.88E-02	1.11E-01
			12252600	Flight crew's air/ground/air communication	2.94E-01	5.56E-01
			22080101	Air traffic management's internal coordination of civil sectors in the same unit	5.88E-02	1.11E-01
			24010101	Air traffic control use of phraseology	5.88E-02	1.11E-01
			24010102	Air traffic control use of readback/hearback error detection	3.53E-01	6.67E-01
			24010103	Blocked communication	1.18E-01	2.22E-01
			24010107	Air traffic control requirement for the acknowledgement of information by the flight crew	5.88E-02	1.11E-01
			24010108	Air traffic control requirement for the acknowledgement of information by the air traffic control officer	5.88E-02	1.11E-01
			24010301	Frequency selection in the air traffic control communication	5.88E-02	1.11E-01
			25050000	Air traffic management service personnel operating procedures/instructions	5.88E-02	1.11E-01
2020400	Controlled/restricted airspace infringement	1.18E-01	12251600	Flight crew's action in respect to air traffic control procedure	5.88E-02	5.00E-01
			12252400	Flight crew's action in respect to procedure for transfer to visual flight	5.88E-02	5.00E-01
			22060100	Air traffic management's monitoring of aircraft	5.88E-02	5.00E-01

INCIDENT MODELLING

Adverse Events (E)	Event Definition	P(E)	Descriptive Factors (DF)	Descriptive Factor Definition	P(DF)	P(DF E)
2020508	Clearance deviation – approach	1.18E-01	24010107	Air traffic control requirement for the acknowledgement of information by the flight crew	5.88E-02	5.00E-01
			12251500	Flight crew's action in respect to air traffic control clearance	5.88E-02	5.00E-01
			23020400	Air traffic control use of clearance procedure	5.88E-02	5.00E-01
2100200	Diversion due to operational decision	5.88E-02	24010107	Air traffic control requirement for the acknowledgement of information by the flight crew	5.88E-02	5.00E-01
			12251500	Flight crew's action in respect to air traffic control clearance	5.88E-02	1.00E+00
4010100	Air Navigation Services operational communications relate	2.94E-01	12252600	Flight crew's air/ground/air communication	5.88E-02	2.00E-01
			22080101	Air traffic management's internal coordination of civil sectors in the same unit	1.18E-01	4.00E-01
			22080102	Air traffic management's internal coordination of military sectors in the same unit	5.88E-02	2.00E-01
			22080202	Air traffic management's coordination with an adjacent military unit	5.88E-02	2.00E-01
			24010102	Air traffic control use of readback/hearback error detection	5.88E-02	2.00E-01
			24010106	Air traffic control transfer of communication	5.88E-02	2.00E-01
			24010204	Communication technique used by air traffic management in ground to ground communication	5.88E-02	2.00E-01
			24010703	Air traffic control provision of flight information	5.88E-02	1.00E+00
4010200	Air Navigation Services operational information provisions	5.88E-02	22060100	Air traffic management's monitoring of aircraft	1.76E-01	3.00E-01
			22080303	Revision of air traffic management's coordination procedures	5.88E-02	1.00E-01
			22100600	Briefing for the hand-over/take-over	5.88E-02	1.00E-01
			22100700	Familiarization with traffic during the hand-over/take-over	5.88E-02	1.00E-01
			22120100	Air traffic management's strategic planning for conflict detection	1.76E-01	3.00E-01
4010400	Air Navigation Services conflict detection and resolution related event	5.88E-01				

Adverse Events (E)	Event Definition	P(E)	Descriptive Factors (DF)	Descriptive Factor Definition	P(DF)	P(DF E)
4010600	Air Navigation Services handing over/taking over procedure	1.18E-01	22120200	Air traffic management's tactical execution of the conflict detection strategy	2.35E-01	4.00E-01
			22130101	Air traffic management's horizontal conflict resolution by radar vectoring/monitoring	5.88E-02	1.00E-01
			23010300	Clearance procedure	5.88E-02	1.00E-01
			24010108	Air traffic control requirement for the acknowledgement of information by the air traffic control officer	5.88E-02	1.00E-01
			24010604	Air traffic control provision of a short term conflict alert (STCA) warning	5.88E-02	1.00E-01
			27030000	Air traffic control monitoring of sector traffic load	5.88E-02	1.00E-01
			22080101	Air traffic management's internal coordination of civil sectors in the same unit	1.18E-01	1.00E+00
			23010300	Clearance procedure	5.88E-02	5.00E-01
			22060100	Air traffic management's monitoring of aircraft	5.88E-02	1.00E+00
			24010705	Air traffic control provision of delay related information	5.88E-02	1.00E+00
4050400	Failure of data processing	5.88E-02	12251500	Flight crew's action in respect to air traffic control clearance	5.88E-02	2.00E-01
4070400	Air space capacity reduction	2.94E-01	22080103	Air traffic management's internal coordination of positions in civil sectors in the same unit	5.88E-02	2.00E-01
			22100300	Airspace during the hand-over/take-over	5.88E-02	2.00E-01
			24010107	Air traffic control requirement for the acknowledgement of information by the flight crew	5.88E-02	2.00E-01
			27030000	Air traffic control monitoring of sector traffic load	1.18E-01	4.00E-01
			27050200	Factors relating coordination with air traffic flow management	5.88E-02	2.00E-01
			41100300	Runway obstruction	5.88E-02	2.00E-01
			52020400	Tailwind	5.88E-02	2.00E-01
			52031400	Cloud amount restricting visibility	5.88E-02	2.00E-01

Table 5-5 – CPT of Events and Descriptive Factors under Scenario of LOS in Civil/Commercial Aviation

Figure 5-4 – BN model for serious LOS incidents in civil/commercial aviation

Figure 5-5 – GeNIe output of events and DFs during first three years

Figure 5-6 – Affected DFs likelihood estimation when events with present = 100%

5.3.3. BN Model Sensitivity Analysis

Three cases have been considered for sensitivity analysis to identify sensitive parameters in the BN model. All analyses are done using the BN model with the dataset $\{U_{anal.}\}$ and the default algorithm applied in GeNIe proposed by Kjaerulff and van der Gaag.

1. The sensitivity analysis of DFs related to A/C or Flight Crew.

All DFs related to A/C or Flight Crew are selected as targets. Figure 5-8 presents the results of this analysis, the following events are shown in dark red and identified as the most sensitive parameters:

- '*A/C communication systems*'
- '*A/C clearance deviation – approach*'
- '*ANS clearance to wrong altitude*'
- '*Controlled/restricted airspace infringement*'
- '*ANS erroneous clearance*'

2. The sensitivity analysis of DFs related to ATM.

All DFs related to ATM are selected as targets. With the results of this analysis presented in Figure 5-9, two events are identified as the most sensitive parameters:

- '*ANS failure of data processing*'
- '*ANS handing over/taking over procedure*'

3. The sensitivity analysis of DFs related to A/C or Flight Crew & ATM.

All DFs related to A/C or Flight Crew and ATM are selected as targets. Figure 5-10 presents the results of this analysis and next conclusion can be summarised comparing with the results of the other two analyses:

- Comparing with the sensitivity analysis of DFs related to A/C or Flight Crew, the event '*ANS erroneous clearance*' is less sensitive and the event '*Communication between pilot and ANS*' is one of the most sensitive parameters in this case.
- Comparing with the sensitivity analysis of DFs related to ATM, the event '*Air space capacity reduction*' is less sensitive in this case.

Figure 5-8 – Sensitivity Analysis with DFs related to A/C or Flight Crew as Targets

Figure 5-9 – Sensitivity Analysis with DFs related to ATM as Targets

Figure 5-10 – Sensitivity Analysis with DFs related to A/C or Flight Crew and ATM as Targets

5.3.4. BN Model Validation

In this validation study, the data of the last year is added into the BN model and K-fold cross-validation is applied, which K is 1000 records generated applying GeNIe and used to run the BN model. The validation accuracy of all 51 nodes is 0.956 and by an individual node is calculated with GeNIe and shown in Table 5-6.

Child Node	Accuracy	Nº Correct Records	Parent Node	Accuracy	Nº Correct Records
12232800	0.950	950/1000	1230000	0.975	975/1000
12251500	0.944	944/1000	2020201	0.939	939/1000
12251600	0.989	989/1000	2020202	0.961	961/1000
12251800	0.985	985/1000	2020300	0.819	819/1000
12252400	0.987	987/1000	2020400	0.972	972/1000
12252600	0.878	878/1000	2020508	0.960	960/1000
22060100	0.889	889/1000	2100200	0.979	979/1000
22080101	0.926	926/1000	4010100	0.921	921/1000
22080102	0.982	982/1000	4010200	0.976	976/1000
22080103	0.978	978/1000	4010400	0.821	821/1000
22080202	0.986	986/1000	4010600	0.963	963/1000
22080303	0.972	972/1000	4050400	0.981	981/1000
22100300	0.987	987/1000	4070400	0.918	918/1000
22100600	0.989	989/1000			
22100700	0.973	973/1000			
22120100	0.924	924/1000			
22120200	0.937	937/1000			
22130101	0.987	987/1000			
23010300	0.962	962/1000			
23020400	0.980	980/1000			
24010101	0.974	974/1000			
24010102	0.860	860/1000			
24010103	0.961	961/1000			

Child Node	Accuracy	Nº Correct Records	Parent Node	Accuracy	Nº Correct Records
24010106	0.992	992/1000			
24010107	0.933	933/1000			
24010108	0.960	960/1000			
24010204	0.986	986/1000			
24010301	0.978	978/1000			
24010604	0.984	984/1000			
24010703	0.954	954/1000			
24010704	0.982	982/1000			
24010705	0.981	981/1000			
25050000	0.949	949/1000			
27030000	0.952	952/1000			
27050200	0.979	979/1000			
41100300	0.984	984/1000			
52020400	0.984	984/1000			
52031400	0.983	983/1000			

Table 5-6 – BN Model Validation Output from GeNIe 2.0

5.4. Analysis and Discussion

A general view of the proposed BN model, Figure 5-11, illustrates the cause-effect relationship between events and DFs. Events which present high probabilities are associated with great numbers of DFs connected, hence the efficiency of barriers which could influence the DFs to reduce event occurrences should be discussed.

Figure 5-11 – Event probabilities and n° of associated DFs

One barrier in the BN model can be interpreted as a factor or a group of factors contributing to an event. The assumption that the activation of barriers is equivalent to the positive contribution of DFs in BN model, leads to a forward conditional probability analysis setting events that present in Figure 5-11 with high likelihood equal to 1 (state = present) in Equation 3. Therefore, the output of DFs with major contribution is located in the BN model and listed in Table 5-7.

Events with P(E = 1)	Descriptive Factors (DFs)	DFs Code	P(DF)
Communication between pilot and ANS	ATC readback / hearback error detection	24010102	Present = 0.69
	Flight crew's air/ground/air communication	12252600	Present = 0.58
	Air traffic management's internal coordination of civil sectors in the same unit	22080101	Present = 0.31
	Air traffic control requirement for the acknowledgement of information by the flight crew	24010107	Present = 0.26
ANS operational communications	Air traffic management's internal coordination of civil sectors in the same unit	22080101	Present = 0.50
	ATC readback / hearback error detection	24010102	Present = 0.48
	Flight crew's air / ground / air communication	12252600	Present = 0.44
ANS conflict detection and resolution	Air traffic management's monitoring of aircraft	22060100	Present = 0.42
	Air traffic management's tactical execution of the conflict detection strategy	22120200	Present = 0.40
	Air traffic management's strategic planning for conflict detection	22120100	Present = 0.34
Air space capacity reduction	Air traffic control monitoring of sector traffic load	27030000	Present = 0.44
	Air traffic control requirement for the acknowledgement of information by the flight crew	24010107	Present = 0.33
	Flight crew's action in respect to air traffic control clearance	12251500	Present = 0.29

Table 5-7 – DFs with major contribution when associated event present = 100%

Setting these detected DFs as absent in the BN model to simulate barriers in an active state for each event and following the backward conditional probability analysis with Equation 4, the likelihood of selected events are recalculated. Thus the efficiency of assumptive barriers is evaluated checking the variation to events probability in Table 5-8.

Events with P(E = 1)	P(E) with barrier absented	P(E) with barrier activated
Communication between pilot and ANS	Present = 0.53	Present = 0.12
ANS operational communications	Present = 0.29	Present = 0.14
ANS conflict detection and resolution	Present = 0.59	Present = 0.30
Air space capacity reduction	Present = 0.29	Present = 0.14

Table 5-8 – The reduction of event likelihoods with barriers activated

The proposed BN model highlights the examination of barrier efficiency once factors with major contribution of incidents are located. Barriers that are implemented in the ATM system

should be identified by using authentic cases. This identification follows the '*absent/failed barriers*' analysis in SOAM model [32].

The incidents analysis route that this research has been following is derived from the basis of SOAM model and supplemented with ADREP taxonomy. Comparing the SOAM model with the process of analysis employed in this work and BN modelling, the following differences should be considered for discussion:

- SOAM model presents a systematic diagram for incident analysis, while our process of analysis with ADREP taxonomy introduces a sequential diagram incident analysis based on cause-effect relationship.
- With ADREP taxonomy, common causes and events are generalised, even collected with encoding for database creation, features as a supplement to SOAM model from the further software design point of view.
- BN model based on empirical evidence plays a role in order to simplify the recognition of causes and events, as well as the efficiency check of barriers that are provided by SOAM model.

However, this BN model presents next limitations that should be taken into consideration:

- The BN model is created based on a combination of expert-built and frequency data-driven. The BN model construction is influenced by opinion and analysis of experts during the incident investigation. For this reason, as Ferrante et. al. [64] discussed in their research work, a group of experts and cross-validation are required during the detection of events and factors.
- The continuing update of the BN model is required to provide high accuracy upon the predictive analysis. The BN predictive capacity opens the development of barriers monitoring focused on critical factors of the ATM system, nevertheless, in practices, the accuracy of this monitoring should be kept with incident database updated.

Finally, the impact evaluation of new technologies or new ATM systems implementation using our proposed BN model should be mentioned. Brooker [89] exposed some examples

of controller and pilot mistakes, that the SESAR system design does safely deal with. These kinds of errors in terms of ADREP taxonomy are identified as DFs in our proposed BN model such as '*ATM monitoring aircraft*', '*ATC monitoring of sector traffic load*', '*ATC clearance procedure*' and '*ATC readback/hearback error detection*'. If the probability of occurrence in these DFs is reduced, we would be able to observe what kind of adverse events and how they are affected, also how much their probability of occurrences could be changed under SESAR operational environment.

5.5. Conclusion

Both processes, analysis and modelling, have demonstrated the detection of precursors for LOS serious incidents from simple reports and the construction of BN model for future incident prediction and barrier evaluation.

The manner in which the analysis presented in this work is carried out for two purposes:

- i. The procedure is focused on providing a chronological vision related to incident scenarios that can be separated by events and factors. Hence, the traceability between report and analysis is preserved;
- ii. As a result of the first purpose, the analysis result is stored in database format for posterior BN model creation.

During the process of modelling, the BN model is developed using a system management of incidents given-in-experience. In this BN model, two benefits are considered:

- a. Within the presented case study, the correlation between events and factors are set up and achieves predictive property, which assists in identifying a set of events and factors which could be occurred with high probability in a new incident case.

As well as other predictive BN models, uncertainties are inevitable in this BN model. However, the degree of uncertainties can be reduced only if the model is updated with new incident cases constantly, then the location of a contrastive event or factor to incidents should be more accurate.

- b. During the BN model analysis, the barrier question is treated. In this research, we have considered that the importance of barrier imposition is not only to reduce the occurrence probability of an event, or a set of them, but also to evaluate the impact on imposed barriers into a complex system such as the ATM. The efficiency is observed based on the variation of event likelihood when the simulated barrier is activated in the BN model. However, the simulated barrier concept is created based on DFs with a high probability of occurrence to condition the likelihood of events. The differences between real barriers and simulated barriers should be discussed in the future work,

especially those barriers provided by new technologies implemented under the SESAR environment should be analysed quantitatively with real cases.

In summary, the BN model provides an in depth diagnostic to LOS serious incident scenario and predictive capacity for new incident analysis, facilitating official investigations. Additionally, the barrier concept introduced above and using the BN model, behaviour and efficiency can be analysed.

INTENTIONALLY LEFT BLANK

Chapter 6.

6. ACCIDENT PREDICTION

Ad Meliora

(towards better things)

This chapter aims to explore BN and IT for precursor-based risk analysis of major accidents known as MAC in the aviation sector. One proposed method combines principles from Quantitative Risk Analysis, Bayesian Network modelling and Information Theory, to infer the likelihood of catastrophic accidents using a set of LOS data collected during a period of four consecutive years in Spanish airspace.

6.1. Introduction

This work attempts to model the probability of severe LOS near accidents combining the BN and IT. As the starting step, the BN model is used to detect LOS contributing factors and establish the multi-dependent relationship between them. This technique is widely used for risk analysis [90] [91] and decision-making [92] [93] in complex systems, i.e. the air traffic management system. The uncertainty contained in LOS scenarios makes the BN model as the preferred candidate for this case study. As the next step of this study, IT is applied to identify the information provided by LOS precursors. The combination of both techniques allows the use of LOS precursors to portray perceptive warning scenarios, which might forecast a near accident and anticipate a MAC accident.

6.2. Methodology of Accident Prediction

Figure 6-1 presents the proposed methodology following the indicated main phases and steps. The methodology is applied with causal-effect analysis for serious and major LOS incidents as the starting point. In this first phase, from the analysis related to the notification of occurrences and investigation reports, it aims to detect all precursors leading to serious and major LOS incidents. During this phase, following a determined analysis procedure, data collected from serious and major incident reports are identified into events and factors, which are interpreted as precursors to accidents that might occur in the future. For the accomplishment of this objective, standardised analysis methodologies and taxonomies are applied in this process.

During the second phase, a BN model is developed and validated using the correlation between events and factors as the basis. This model provides a quantitative cause-effect map that recreate serious and major LOS scenarios. The model also contains the estimated likelihood based on the number of reports investigated, the new relationships that are established as the target of this model and the known relationships that were detected by previous researchers.

In the third phase, the concept of entropy and the principle of Information Theory are used to assess the precursor which are most correlated to when a serious or major LOS incident occurs. In the last phase, this information is applied to define predictive scenarios. Additionally, Receiver Operating Characteristic (ROC) curve is used to evaluate the most effective predictive scenario.

In the following sections, the preceding steps are described in more detail.

Figure 6-1 – Methodology for accident prediction

6.2.1. Causal-effect analysis for serious & major LOS incidents

This first phase consists of four steps: 1) selection of LOS incident reports, 2) LOS incident analysis, 3) LOS precursor identification and, 4) precursor storage as mathematical parameter in the incident database. These steps 1 to 4 follow the same process of analysis explained in section 5.2.1.

With this procedure, incident scenarios can be presented by a chronological vision and separated by events and factors. Hence, the traceability between report and analysis is preserved.

6.2.2. Development and validation of the BN model

The aim of this second phase is developing a model that would have a predictive feature to determine the adverse events and associated causes in future ATM incidents (step 5). This step 5 follows the same process of modelling detailed in section 5.2.2.

6.2.3. Information theory application

Common causes or influential factors are presented in MAC accidents and LOS incidents in the form of initiating events and factors. The occurrence of a serious or major LOS and its causes would contain information related to the final accident. This relation between causes can be quantified using the concept of mutual information. Among the LOS causes, which

with the highest mutual information are more informative, i.e. if one cause presents itself, it reduces the uncertainty related to the potential occurrences leading to an accident (step 6).

If a LOS is considered as a random variable with mass function $P(z)$, the amount of uncertainty associated with this value 'z' can be measured by the entropy $H(Z)$ applying the next equation:

$$\text{Equation 5: } H(Z) = -\sum_{z \in Z} P(z) \log P(z)$$

The conditional entropy of Z known the probability of the cause Y is another random variable defined as:

$$\text{Equation 6: } H(Z|Y) = -\sum_{z,y} P(z,y) \log \frac{P(z,y)}{P(y)}$$

The mutual information of Z and Y, $I(Z, Y)$, can be defined in the uncertainty of Z given the observation of Y:

$$\text{Equation 7: } I(Z, Y) = H(Z) - H(Z|Y) = \sum_{z,y} P(z,y) \log \frac{P(z,y)}{P(z)P(y)} = \sum_{z,y} P(y)P(z|y) \log \frac{P(z|y)}{P(z)}$$

The calculation of conditional probabilities is accessible from the corresponding BN, which allows a quick and easy update of the mutual information when a new set of data become available.

6.2.4. Development and evaluation of predictive scenarios

The identification of influential factors (events and factors) that contain the most relevant information can be used to establish the probability of an accident. The most informative influential factors could be interpreted as a binary classifier.

Different predictive scenarios could be developed using these influential factors (step 7) and their performances are assessed by a ROC curve (step 8), which is a graphical tool to evaluate the performance of a model—especially a binary classifier, based on the threshold of discrimination. However, the most effective predictive scenario is required to identify for performing this analysis (step 9).

In Figure 6-2, a ROC curve presents the True Positive Rate versus the False Positive Rate, with FPR on the horizontal axis and TPR on the vertical axis. The diagonal line, also called line of no-discrimination, divides the space into three areas: the space above the no-

discrimination line that represents good predictions; the space below the no-discrimination line that represents poor predictions; and the points along the line of no-discrimination that represent a random result.

For a determined threshold, TPR is the ratio of actual positives that are correctly identified as indicated in Equation 8. FPR is the ratio of actual false positives that are correctly identified as indicated in Equation 9.

Equation 8: $TRP = \frac{TP}{TP+FN}$

Equation 9: $FPR = \frac{FP}{FP+TN}$

TP is true positives, FP is false positives, FN is false negatives and TN is true negatives.

Finally, the accuracy of the classifier can be defined as follows:

Equation 10: $ACC = \frac{TP+TN}{TP+FP+TN+FN}$

Figure 6-2 – ROC curve for a binary classifier

6.3. Case study: assessment of four years of LOS in Spanish Airspace

A sample of the proposed methodology application, a set of data of LOS occurrences during four consecutive years is considered in this case study. According to the procedure illustrated in Figure 6-1, the application implies three basic phases and nine detailed steps in total.

For the purpose of clarity, this chapter is divided into three main sections, which detail all steps followed in each phase:

- Phase 1: Causal-effect analysis for serious & major LOS incidents
- Phase 2: Development and validation of the BN model
- Phase 3: Information theory application

6.3.1. Case study phase 1: Causal-effect analysis for serious & major LOS incidents (steps 1 thru 4)

Firstly, historical data and LOS reports are selected for this analysis (step 1). All serious and major incidents occurred in Spanish airspace and reported in a period of four years are considered for this analysis. The number of cases have been analysed is illustrated in Figure 6-3.

Previous to precede the incident analysis, incident reports are selected following the next criteria:

- Selection by incident severity: serious (severity A) or major (severity B) incident;
- Selection by incident category: LOS or SMI;
- Selection by type of flight: limited only to commercial aircraft involved in the incident scenario;
- Selection by operating phase: when the incident occurred, none of the involved aircraft was operating at the final approach phase or before achieving the second segment of the take-off.

Figure 6-3 – Spanish investigated incidents of severity A & B during four consecutive years

These datasets contain events and factors extracted from reports (step 2) as results of the analysis, which depict a causal-effect map of selected LOS. Precursors related to loss of separation incidents are identified, filtered (step 3), and registered as mathematical parameters in an incident database (Step 4).

6.3.2. Case study phase 2: Development and validation of the BN model (step 5)

The development and validation of the BN model that is constructed based on serious and major incident data present the same processes detailed in section 5.3.2. As the same result, the BN model is divided into the same five groups. In general, into these five groups, three categories of nodes can be considered in ATM incidents.

- Adverse events. They are interpreted as effects or stages that establish the LOS incident.
- Influential causes. Influential factors are extracted from incident reports and can be considered as DFs and EFs, which are causes of failures. Then, the precursors are identified with these three components: events, DFs and EFs.
- The type of LOS at each incident. LOS is classified with the associated severity.

For BN structure learning, two kinds of learning are presented in the BN structure. One consists of verifying the structure of BN and remove weak connections between nodes by massive data sets. The other involves deciding the BN structure by data reasoning. In this proposed BN model, the structure has been decided based on the study of phase 1 and expert knowledge.

Table 6-1 and Table 6-2 present the CPT of the correlation between events and DFs into serious and major LOS scenario. Their derived DAG is represented in Figure 6-4 as a correlation map. The proposed BN model is illustrated in Figure 6-5.

For BN parameters learning, the Bayes method uses prior density and posterior density to learn and assess parameters. BN also uses the above process to learn parameters after collecting and accumulating relevant data. In the practical application, conjugate prior is used to simplify the parameter learning of BN. In Bayesian theory, the conjugate means that the posterior distributions, as well as the prior distributions, are in the same probability distribution family. Then the prior and posterior can be identified as a conjugate distributions; moreover, the likelihood function of the prior is identified as conjugate prior. A conjugate prior is an algebraic convenience, providing a closed-form expression for the posterior. In this proposed BN model, prior probabilities and posterior probabilities have the same distribution family – Dirichlet distribution.

For BN validation, the procedure of validation is the same described in 5.3.4. For this proposed model, K-fold cross validation is applied, one data file of 1000 records is generated by GeNIe and used to compile the validation. The validation accuracy of all nodes is 0.945 and, for the individual node, it is calculated with GeNIe.

For BN sensitivity analysis. A simple sensitivity analysis with DFs as the target is done to identify highly sensitive parameters, which affect the reasoning results significantly. As results, Figure 6-6 shows the most sensitive parameters of the network when DFs related to Flight Crew-ATM are identified as target and, Figure 6-7 presents the most sensitive parameters with DFs related to both Flight Crew and ATM set as the target. In both figures, it can be observed that the DFs with low likelihood are less sensitive and cause less impact on

their corresponding events and, on the contrary, the DFs with high likelihood present more influence over events in the BN model.

ACCIDENT PREDICTION

Adverse Events (E)	Event Definition	P(E)	P(E Severity)	Descriptive Factors (DF)	Descriptive Factor Definition	P(DF)	P(DF E)
1230000	Communication systems	1.15E-02	7.14E-02	12232800	Pilot's operation of communication equipment	1.15E-02	5.00E-01
2020201	ANS erroneous clearance	3.45E-02	2.14E-01	22060100	ATM's monitoring of A/C	1.15E-02	1.00E-01
				24010703	ATC provision of flight information	1.15E-02	1.00E-01
				25050000	ATM service personnel operating procedures/instructions	2.30E-02	2.00E-01
2020202	ANS clearance to wrong altitude	1.15E-02	7.14E-02	24010704	ATC provision of a minimum safe flight level/altitude/height/sector altitude	1.15E-02	6.67E-02
2020300	Communication between pilot and ANS	6.90E-02	4.29E-01	12251800	Pilot's radiotelephony phraseology	1.15E-02	5.56E-02
				12252600	Pilot's air/ground/air communication	4.60E-02	2.22E-01
				22080101	ATM's internal coordination of civil sectors in the same unit	2.30E-02	1.11E-01
				24010101	ATC use of phraseology	1.15E-02	5.56E-02
				24010102	ATC use of readback/hearback error detection	4.60E-02	2.22E-01
				24010103	Blocked communication	2.30E-02	1.11E-01
				24010107	ATC requirement for the acknowledgement of information by the Pilot	1.15E-02	5.56E-02
				24010301	ATC requirement for the acknowledgement of information by the ATCO	1.15E-02	5.56E-02
2020508	Clearance deviation - approach	1.15E-02	7.14E-02	23020400	ATC use of clearance procedure	1.15E-02	3.33E-01
4010100	ANS operational communications	2.30E-02	1.43E-01	12252600	Pilot's air/ground/air communication	1.15E-02	6.67E-02
				22080101	ATM's internal coordination of civil sectors in the same unit	1.15E-02	6.67E-02
				24010102	ATC use of readback/hearback error detection	1.15E-02	6.67E-02
4010400	ANS conflict detection and resolution	1.38E-01	8.57E-01	22060100	ATM's monitoring of A/C	3.45E-02	5.26E-02
				22080303	Revision of ATM's coordination procedures	1.15E-02	1.75E-02
				22100600	Briefing for the hand-over/take-over	1.15E-02	1.75E-02
				22100700	Familiarization with traffic during the hand-over/take-over	1.15E-02	1.75E-02
				22120100	ATM's strategic planning for conflict detection	5.75E-02	8.77E-02

ACCIDENT PREDICTION

Adverse Events (E)	Event Definition				P(E)	P(E Severity)	Descriptive Factors (DF)	Descriptive Factor Definition	P(DF)	P(DF E)
4010600	ANS handing over/taking over procedure				3.45E-02	2.14E-01	22120200	ATM's tactical execution of the conflict detection strategy	6.90E-02	1.05E-01
							22130101	ATM's horizontal conflict resolution by radar vectoring/monitoring	1.15E-02	1.75E-02
							23010300	Clearance procedure	3.45E-02	5.26E-02
							24010604	ATC provision of a short term conflict alert (STCA) warning	2.30E-02	3.51E-02
							27030000	ATC monitoring of sector traffic load	1.15E-02	1.75E-02
4050300	Failure of surveillance				1.15E-02	7.14E-02	22080101	ATM's internal coordination of civil sectors in the same unit	3.45E-02	4.29E-01
							23010300	Clearance procedure	1.15E-02	1.43E-01
							22060100	ATM's monitoring of A/C	1.15E-02	5.00E-01
4070400	Air space capacity reduction				4.60E-02	2.86E-01	24010705	ATC provision of delay related information	1.15E-02	5.00E-01
							22080103	ATM's internal coordination of military sectors in the same unit	1.15E-02	1.25E-01
							22100300	Airspace during the hand-over/take-over	1.15E-02	1.25E-01
							27030000	ATC monitoring of sector traffic load	2.30E-02	2.50E-01
							27050200	Factors relating coordination with ATFM	1.15E-02	1.25E-01
							41100300	Runway obstruction	1.15E-02	1.25E-01
							52020400	Tailwind	1.15E-02	1.25E-01
							52031400	Cloud amount restricting visibility	1.15E-02	1.25E-01

Table 6-1 – CPT of events and descriptive factors under scenario of LOS in commercial aviation – Severity A

ACCIDENT PREDICTION

Adverse Events (E)	Event Definition	P(E)	P(E Severity)	Descriptive Factors (DF)	Descriptive Factor Definition	P(DF)	P(DF E)
1230000	Communication systems	1.15E-02	1.37E-02	21010900	Headsets	1.15E-02	5.00E-01
				24010103	Blocked communication	1.15E-02	5.00E-01
2020201	ANS erroneous clearance	8.05E-02	9.59E-02	25050000	ATM service personnel operating procedures/instructions	5.75E-02	5.00E-01
				27030000	ATC monitoring of sector traffic load	2.30E-02	2.00E-01
				24010105	ATC call-sign confusion	1.15E-02	1.00E-01
				23020400	ATC use of clearance procedure	1.15E-02	1.00E-01
				12230900	Pilot's operation of emergency brakes	1.15E-02	1.00E-01
				23020700	ATC use of descent procedure	1.15E-02	1.00E-01
				22060100	ATM's monitoring of A/C	1.15E-02	1.00E-01
2020202	ANS clearance to wrong altitude	1.61E-01	1.92E-01	25050000	ATM service personnel operating procedures/instructions	1.15E-01	6.67E-01
				22120100	ATM's strategic planning for conflict detection	1.15E-02	6.67E-02
				27030000	ATC monitoring of sector traffic load	2.30E-02	1.33E-01
				23020400	ATC use of clearance procedure	1.15E-02	6.67E-02
				12240600	The rate of descent of the aircraft	1.15E-02	6.67E-02
				22060100	ATM's monitoring of A/C	5.75E-02	3.33E-01
				23020500	ATC use of climb procedure	1.15E-02	6.67E-02
				24010105	ATC call-sign confusion	1.15E-02	6.67E-02
2020300	Communication between pilot and ANS	1.38E-01	1.64E-01	12252600	Pilot's air/ground/air communication	4.60E-02	2.22E-01
				24010102	ATC use of readback/hearback error detection	8.05E-02	3.89E-01
				12251800	Pilot's radiotelephony phraseology	2.30E-02	1.11E-01
				24010101	ATC use of phraseology	4.60E-02	2.22E-01
				52031600	Thunderstorm	1.15E-02	5.56E-02
				12251400	Pilot's action in respect to instruction	1.15E-02	5.56E-02
				24010105	ATC call-sign confusion	1.15E-02	5.56E-02
				22060200	ATM's monitoring of frequencies	1.15E-02	5.56E-02

ACCIDENT PREDICTION

Adverse Events (E)	Event Definition	P(E)	P(E Severity)	Descriptive Factors (DF)	Descriptive Factor Definition	P(DF)	P(DF E)
2020505	Clearance deviation - take-off	3.45E-02	4.11E-02	25050000	ATM service personnel operating procedures/instructions	1.15E-02	5.56E-02
				23020600	ATC use of departure procedure	1.15E-02	3.33E-01
				22100600	Briefing for the hand-over/take-over	1.15E-02	3.33E-01
				23020500	ATC use of climb procedure	1.15E-02	3.33E-01
				22050100	A/C performance differences	2.30E-02	6.67E-01
2020506	Clearance deviation - en-route	6.90E-02	8.22E-02	23020400	ATC use of clearance procedure	1.15E-02	3.33E-01
				23020700	ATC use of descent procedure	2.30E-02	3.33E-01
				24010703	ATC provision of flight information	1.15E-02	1.67E-01
				23020500	ATC use of climb procedure	3.45E-02	5.00E-01
				22090000	ATM's traffic transfer	1.15E-02	1.67E-01
				12251800	Pilot's radiotelephony phraseology	1.15E-02	1.67E-01
				22100600	Briefing for the hand-over/take-over	1.15E-02	1.67E-01
				52020400	Tailwind	1.15E-02	1.67E-01
				23010300	Clearance procedure	1.15E-02	1.67E-01
				23010200	AWY/Route approach procedure	1.15E-02	1.67E-01
2020508	Clearance deviation - approach	2.30E-02	2.74E-02	24010101	ATC use of phraseology	1.15E-02	3.33E-01
				12210900	Pilot's obstacle clearance judgement	1.15E-02	3.33E-01
				12251400	Pilot's action in respect to instruction	1.15E-02	3.33E-01
				52031400	Cloud amount restricting visibility	1.15E-02	3.33E-01
				22050100	A/C performance differences	1.15E-02	3.33E-01
2020509	Clearance deviation - holding	1.15E-02	1.37E-02	23020400	ATC use of clearance procedure	1.15E-02	1.00E+00
2020513	Clearance deviation - special procedure	2.30E-02	2.74E-02	12251400	Pilot's action in respect to instruction	2.30E-02	1.00E+00
				24010102	ATC use of readback/hearback error detection	2.30E-02	1.00E+00
2020517	Deviation from clearance - assigned flight level	1.03E-01	1.23E-01	12251500	Pilot's action in respect to ATC clearance	8.05E-02	7.78E-01
				52020500	Crosswind	2.30E-02	2.22E-01
				22060100	ATM's monitoring of A/C	1.15E-02	1.11E-01

ACCIDENT PREDICTION

Adverse Events (E)	Event Definition	P(E)	P(E Severity)	Descriptive Factors (DF)	Descriptive Factor Definition	P(DF)	P(DF E)
				12232800	Pilot's operation of communication equipment	1.15E-02	1.11E-01
				24010102	ATC use of readback/hearback error detection	1.15E-02	1.11E-01
				12251400	Pilot's action in respect to instruction	1.15E-02	1.11E-01
				52031600	Thunderstorm	1.15E-02	1.11E-01
				11222000	Speed-attitude correction system	1.15E-02	1.11E-01
				12230900	Pilot's operation of emergency brakes	1.15E-02	1.11E-01
				12252200	Pilot's action in respect to standard operating procedure	1.15E-02	1.11E-01
2020519	Deviation from clearance - assigned or specified speed	2.30E-02	2.74E-02	25050000	ATM service personnel operating procedures/instructions	1.15E-02	1.11E-01
				12251500	Pilot's action in respect to ATC clearance	1.15E-02	5.00E-01
				12240700	The flying speed of the aircraft	1.15E-02	5.00E-01
2020522	Deviation from clearance - climb/descent conditional clearance	1.15E-02	1.37E-02	12252600	Pilot's air/ground/air communication	1.15E-02	5.00E-01
				24010101	ATC use of phraseology	1.15E-02	1.00E+00
2020805	Deviation from approach procedure	3.45E-02	4.11E-02	12210500	Pilot's perception of visual/oral warning	1.15E-02	1.00E+00
				24010703	ATC provision of flight information	2.30E-02	6.67E-01
				23020300	ATC use of approach procedure	3.45E-02	1.00E+00
2100100	Diversion due to weather conditions	3.45E-02	4.11E-02	24010101	ATC use of phraseology	1.15E-02	3.33E-01
				52031400	Cloud amount restricting visibility	1.15E-02	3.33E-01
				52010200	Instrument meteorological conditions	1.15E-02	3.33E-01
				52021200	Turbulence in cloud	1.15E-02	3.33E-01
2170200	Wrong runway selected	1.15E-02	1.37E-02	21040200	ATM's information data system	1.15E-02	1.00E+00
				24010304	Information input error in the ATC operations	1.15E-02	1.00E+00
4010100	ANS operational communications	1.49E-01	1.78E-01	22080203	ATM's coordination with an adjacent civil sector	6.90E-02	4.00E-01
				22090000	ATM's traffic transfer	6.90E-02	4.00E-01

ACCIDENT PREDICTION

Adverse Events (E)	Event Definition	P(E)	P(E Severity)	Descriptive Factors (DF)	Descriptive Factor Definition	P(DF)	P(DF E)
4010200	ANS operational information provisions	2.30E-02	2.74E-02	22080101	ATM's internal coordination of civil sectors in the same unit	2.30E-02	1.33E-01
				24010703	ATC provision of flight information	1.15E-02	6.67E-02
				23020700	ATC use of descent procedure	1.15E-02	6.67E-02
				22080103	ATM's internal coordination of military sectors in the same unit	1.15E-02	6.67E-02
				22100600	Briefing for the hand-over/take-over	2.30E-02	1.33E-01
				22080201	ATM's coordination with an adjacent civil unit	1.15E-02	6.67E-02
				25050000	ATM service personnel operating procedures/instructions	1.15E-02	6.67E-02
				24010106	ATC transfer of communication	1.15E-02	6.67E-02
				24010703	ATC provision of flight information	2.30E-02	1.00E+00
				27030000	ATC monitoring of sector traffic load	1.15E-02	5.00E-01
4010300	ANS separation provision	2.30E-02	2.74E-02	24010703	ATC provision of flight information	2.30E-02	1.00E+00
				21020103	ATM's use of the instrument landing system	1.15E-02	5.00E-01
				23020300	ATC use of approach procedure	1.15E-02	5.00E-01
4010400	ANS conflict detection and resolution	5.17E-01	6.16E-01	22060100	ATM's monitoring of A/C	1.15E-02	5.00E-01
				23020700	ATC use of descent procedure	1.15E-02	5.00E-01
				23010201	Surveillance radar element of a precision approach radar system approach	1.15E-02	1.75E-02
				22130101	ATM's horizontal conflict resolution by radar vectoring/monitoring	1.26E-01	1.93E-01
				24010703	ATC provision of flight information	4.60E-02	7.02E-02
				23010300	Clearance procedure	1.15E-02	1.75E-02
				22060100	ATM's monitoring of A/C	5.75E-02	8.77E-02
				23020700	ATC use of descent procedure	8.05E-02	1.23E-01
				22110200	ATM's updating of a flight plan	1.15E-02	1.75E-02
				23020600	ATC use of departure procedure	1.15E-02	1.75E-02

ACCIDENT PREDICTION

Adverse Events (E)	Event Definition	P(E)	P(E Severity)	Descriptive Factors (DF)	Descriptive Factor Definition	P(DF)	P(DF E)
4010500	ANS handling of accidents / incidents / emergency	1.15E-02	1.37E-02	23020400	ATC use of clearance procedure	4.60E-02	7.02E-02
				27060100	ATC assistance to the ATC in recovering control of traffic	2.30E-02	3.51E-02
				22120100	ATM's strategic planning for conflict detection	3.45E-02	5.26E-02
				23020300	ATC use of approach procedure	2.30E-02	3.51E-02
				24010102	ATC use of readback/hearback error detection	2.30E-02	3.51E-02
				22120200	ATM's tactical execution of the conflict detection strategy	2.30E-02	3.51E-02
				22130200	ATM's vertical conflict resolution	8.05E-02	1.23E-01
				12252600	Pilot's air/ground/air communication	1.15E-02	1.75E-02
				24010604	ATC provision of a short term conflict alert (STCA) warning	5.75E-02	8.77E-02
				52031600	Thunderstorm	1.15E-02	1.75E-02
				22090000	ATM's traffic transfer	1.15E-02	1.75E-02
				22130300	ATM's conflict resolution by planned controller action	1.15E-02	1.75E-02
				24010101	ATC use of phraseology	1.15E-02	1.75E-02
				27030000	ATC monitoring of sector traffic load	2.30E-02	3.51E-02
				24010605	ATC provision of airborne proximity warning	1.15E-02	1.75E-02
				12251500	Pilot's action in respect to ATC clearance	1.15E-02	1.75E-02
				25050000	ATM service personnel operating procedures/instructions	3.45E-02	5.26E-02
				24010105	ATC call-sign confusion	1.15E-02	1.75E-02
				23020800	ATC use of emergency procedure	1.15E-02	1.00E+00
				22060100	ATM's monitoring of A/C	1.15E-02	1.00E+00
				26070000	ATM handling of A/C unusual/emergency situation	1.15E-02	1.00E+00
				23010700	Emergency procedure	1.15E-02	1.00E+00

ACCIDENT PREDICTION

Adverse Events (E)	Event Definition	P(E)	P(E Severity)	Descriptive Factors (DF)	Descriptive Factor Definition	P(DF)	P(DF E)
4010600	ANS handing over / taking over procedure	4.60E-02	5.48E-02	22080203	ATM's coordination with an adjacent civil sector	2.30E-02	2.86E-01
				25050000	ATM service personnel operating procedures/instructions	1.15E-02	1.43E-01
				27030000	ATC monitoring of sector traffic load	2.30E-02	2.86E-01
				22090000	ATM's traffic transfer	1.15E-02	1.43E-01
				22080101	ATM's internal coordination of civil sectors in the same unit	1.15E-02	1.43E-01
				22100600	Briefing for the hand-over/take-over	1.15E-02	1.43E-01
				27010300	ATC rostering/sector opening in relation to expected traffic	1.15E-02	1.43E-01
4050300	Failure of surveillance	1.15E-02	1.37E-02	21030401	ATM's use of secondary area radar	1.15E-02	5.00E-01
4070400	Air space capacity reduction	4.60E-02	5.48E-02	52010200	Instrument meteorological conditions	1.15E-02	1.25E-01
				27030000	ATC monitoring of sector traffic load	3.45E-02	3.75E-01
				24010301	ATC requirement for the acknowledgement of information by the ATCO	1.15E-02	1.25E-01
				23021100	ATC use of holding procedure	1.15E-02	1.25E-01
				22100300	Airspace during the hand-over/take-over	1.15E-02	1.25E-01

Table 6-2 – CPT of events and descriptive factors under scenario of LOS in commercial aviation – Severity B

Figure 6-4 – BN model for LOS serious & major incidents in commercial aviation

Figure 6-5 – GeNIe output of events and DFs during four consecutive years

Figure 6-6 – Results of the sensitivity analysis with common DFs between A/C and ATM as target

Figure 6-7 – Results of the sensitivity analysis with DFs corresponding to A/C and ATM as target

6.3.3. Case study phase 3: Information theory application (step 6 thru 9)

Once the BN has been validated, the entropy principle could be applied to identify the events and DFs with the most influential contribution to a LOS. Applying Equation 7 for each severity of incidents, the mutual information of the serious/major LOS incidents with their events/DFs are calculated and presented in Figure 6-8 (Step 6). As can be seen, depending on the category of incident severity, the occurrence of the following DFs conveys the most information following the occurrence of a high-severity LOS:

1. Severity A.

- DF '22120200: ATM's tactical execution of the conflict detection strategy'
- DF '22080101: ATM's internal coordination of civil sectors in the same unit'
- DF '22120100: ATM's strategic planning for conflict detection'
- DF '12252600: Pilot's air/ground/air communication'
- DF '24010102: ATC use of readback/hearback error detection'
- DF '22060100: ATM's monitoring of A/C'

2. Severity B.

- DF '25050000: ATM service personnel operating procedures/instructions'
- DF '22130101: ATM's horizontal conflict resolution by radar vectoring/monitoring'
- DF '24010102: ATC use of readback/hearback error detection'
- DF '22060100: ATM's monitoring of A/C'
- DF '27030000: ATC monitoring of sector traffic load'
- DF '12251500: Pilot's action in respect to ATC clearance'
- DF '23020700: ATC use of descent procedure'
- DF '22080203: ATM's coordination with an adjacent civil sector'
- DF '22090000: ATM's traffic transfer'
- DF '24010101: ATC use of phraseology'

Figure 6-8 – Mutual information for each DF in all events of serious & major LOS

The previous DFs are considered as the most informative precursors based on different severities. Different predictive scenarios can be developed using them as the predictive classifier (step 7). The performance of these scenarios should be examined by the ROC curve applying Equation 8 and Equation 9 for calculations of TPR and FPR values. However, data related to all non-incident operations are rarely and difficult to collect well, then for this problem of incomplete data the following conservative criteria are considered in simplifying the estimation of FPR values:

- For scenarios created by individual causes, the value of FPR is considered the same as the TPR value;
- For scenarios created by combined causes, the estimation of FPR in each scenario is the joint of its contributed causes. In other words, $FPR|_{scenario} = \prod_i^n FPR_i|_{cause}$, where n is the number of contributed causes in the scenario.

A total of 11 scenarios in severity A and 19 in severity B have been defined:

1. Severity A.

The first six correspond to each of the precursors independently. The seventh scenario corresponds to the combination of two precursors; the eighth, ninth and tenth scenarios correspond to the combination of three precursors and, finally, the last scenario corresponds to the combination of the six precursors previously identified.

For interpretation of this analysis, scenario 1 is chosen as a sample. In scenario 1 the DFs '*22120200: ATM's tactical execution of the conflict detection strategy*' is used to predict the occurrence of a LOS. TPR and FPR values are calculated according to Equation 8 and Equation 9, where:

- TP is the number of times that both the classifier '*22120200: ATM's tactical execution of the conflict detection strategy*' and a LOS incident with severity A took place.
- FN is the number of times that the classifier '*22120200: ATM's tactical execution of the conflict detection strategy*' did not take place although a LOS incident with severity A occurred.

- FP is the number of times that the classifier '*22120200: ATM's tactical execution of the conflict detection strategy*' took place but no LOS incident with severity A occurred.
- TN is the number of times that neither the classifier '*22120200: ATM's tactical execution of the conflict detection strategy*' took place nor the LOS incident with severity A occurred.

The values of TPR and FPR for this predictive classifier are 0.43, and the ACC of the classifier is 0.57. For the rest of defined scenarios, the values of TPR, FPR and ACC are summarised in Table 6-3.

Scenario	DFs in Each Scenario	TPR	FPR	ACC
1	22120200: ATM's tactical execution of the conflict detection strategy	0.43	0.43	0.57
2	22080101: ATM's internal coordination of civil sectors in the same unit	0.43	0.43	0.57
3	22120100: ATM's strategic planning for conflict detection	0.36	0.36	0.64
4	12252600: Pilot's air/ground/air communication	0.36	0.36	0.64
5	24010102: ATC use of readback/hearback error detection	0.36	0.36	0.64
6	22060100: ATM's monitoring of A/C	0.36	0.36	0.64
7	22120200+22060100: ATM's tactical execution of the conflict detection strategy & ATM's monitoring of A/C	0.64	0.15	0.85
8	22120200+22060100+24010102: ATM's tactical execution of the conflict detection strategy & ATM's monitoring of A/C & ATC use of readback/hearback error detection	0.79	0.06	0.94
9	22120200+22060100+12252600: ATM's tactical execution of the conflict detection strategy & ATM's monitoring of A/C & Pilot's air/ground/air communication	0.79	0.06	0.94
10	22120200+22060100+22120100: ATM's tactical execution of the conflict detection strategy & ATM's monitoring of A/C & ATM's strategic planning for conflict detection	0.79	0.06	0.94
11	22120200+22080101+22120100+12252600+24010102+22060100: ATM's tactical execution of the conflict detection strategy & ATM's internal coordination of civil sectors in the same unit & ATM's strategic planning for conflict detection & Pilot's air/ground/air communication & ATC use of readback/hearback error detection & ATM's monitoring of A/C	0.93	0.00	1.00

Table 6-3 – Evaluation of predictive scenarios – Severity A

2. Severity B.

The first ten correspond to each of the precursors independently. The eleventh scenario is the combination of two most influential precursors; the twelfth scenario is the previous scenario with one influential precursor added, thus successively to the last scenario, which corresponds to the combination of the ten precursors already identified.

As the same in the severity A, scenario 1 is taken as a sample for facilitating the interpretation. In scenario 1 the DFs '25050000: ATM service personnel operating procedures / instructions' is used to predict the occurrence of a LOS. TPR and FPR values are calculated according to Equation 8 and Equation 9, where:

- TP is the number of times that both the classifier '25050000: ATM service personnel operating procedures / instructions' and a LOS incident with severity B took place.
- FN is the number of times that the classifier '25050000: ATM service personnel operating procedures / instructions' did not take place although a LOS incident with severity B occurred.
- FP is the number of times that the classifier '25050000: ATM service personnel operating procedures / instructions' took place but no LOS incident with severity B occurred.
- TN is the number of times that neither the classifier '25050000: ATM service personnel operating procedures / instructions' took place nor the LOS incident with severity B occurred.

The values of TPR and FPR for this predictive classifier are 0.30, and the ACC of the classifier is 0.70. For the rest of defined scenarios, the values of TPR, FPR and ACC are summarised in Table 6-4.

Scenario	DFs in Each Scenario	TPR	FPR	ACC
1	25050000: ATM service personnel operating procedures/instructions	0.30	0.30	0.70
2	22130101: ATM's horizontal conflict resolution by radar vectoring/monitoring	0.15	0.15	0.85
3	24010102: ATC use of readback/hearback error detection	0.16	0.16	0.84
4	22060100: ATM's monitoring of A/C	0.19	0.19	0.81
5	27030000: ATC monitoring of sector traffic load	0.16	0.16	0.84
6	12251500: Pilot's action in respect to ATC clearance	0.12	0.12	0.88
7	23020700: ATC use of descent procedure	0.16	0.16	0.84
8	22080203: ATM's coordination with an adjacent civil sector	0.11	0.11	0.89
9	22090000: ATM's traffic transfer	0.12	0.12	0.88
10	24010101: ATC use of phraseology	0.11	0.11	0.89
11	25050000+23020700: ATM service personnel operating procedures/instructions & ATC use of descent procedure	0.47	0.05	0.95

ACCIDENT PREDICTION

Scenario	DFs in Each Scenario	TPR	FPR	ACC
12	25050000+23020700+24010102: ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection	0.59	0.01	0.99
13	25050000+23020700+24010102+22130101: ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection & ATM's horizontal conflict resolution by radar vectoring/monitoring	0.67	0.00	1.00
14	25050000+23020700+24010102+22130101+22060100: ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection & ATM's horizontal conflict resolution by radar vectoring/monitoring & ATM's monitoring of A/C	0.74	0.00	1.00
15	25050000+23020700+24010102+22130101+22060100+22090000: ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection & ATM's horizontal conflict resolution by radar vectoring/monitoring & ATM's monitoring of A/C & ATM's traffic transfer	0.81	0.00	1.00
16	25050000+23020700+24010102+22130101+22060100+22090000+24010101: ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection & ATM's horizontal conflict resolution by radar vectoring/monitoring & ATM's monitoring of A/C & ATM's traffic transfer & ATC use of phraseology	0.86	0.00	1.00
17	25050000+23020700+24010102+22130101+22060100+22090000+24010101+12251500: ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection & ATM's horizontal conflict resolution by radar vectoring/monitoring & ATM's monitoring of A/C & ATM's traffic transfer & ATC use of phraseology & Pilot's action in respect to ATC clearance	0.90	0.00	1.00
18	25050000+23020700+24010102+22130101+22060100+22090000+24010101+12251500+27030000: ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection & ATM's horizontal conflict resolution by radar vectoring/monitoring & ATM's monitoring of A/C & ATM's traffic transfer & ATC use of phraseology & Pilot's action in respect to ATC clearance & ATC monitoring of sector traffic load	0.93	0.00	1.00
19	25050000+23020700+24010102+22130101+22060100+22090000+24010101+12251500+27030000+22080203: ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection & ATM's horizontal conflict resolution by radar vectoring/monitoring & ATM's monitoring of A/C & ATM's traffic transfer & ATC use of phraseology & Pilot's action in respect to ATC clearance & ATC monitoring of sector traffic load & ATM's coordination with an adjacent civil sector	0.96	0.00	1.00

Table 6-4 – Evaluation of predictive scenarios – Severity B

Generally speaking, the value of TPR reflects the positive conditional probability of classifying/predicting the occurrence of the LOS. The prediction accuracies of the aforementioned scenarios, both severity A and B, are depicted by the value of ACC. Additionally, Figure 6-9 and Figure 6-10 show the ROC curve analysis for all defined scenarios with both severities.

Figure 6-9 – ROC curve using DFs of severity A as precursor data in the prediction of LOS

Figure 6-10 – ROC curve using DFs of severity B as precursor data in the prediction of LOS

In practice, these results lead to great operational usefulness. Based on them, a program that monitors activities of the ATCs could be designed and implemented during standard operations. By monitoring the occurrence of identified DFs, it will be possible to anticipate or predict the occurrence of a high-severity LOS. This program will be extremely cost-effective; instead of complicated and wide supervisory programs. During the activity of an ATC, it will only require the monitoring of a few precursors that have the highest mutual information with the LOS.

6.4. Conclusion

In this work, we have developed a method that combines principles from Quantitative Risk Analysis, Bayesian modelling, and Information Theory, to infer the likelihood of catastrophic accidents based upon precursor data.

The implementation baseline for this methodology details that major accidents and their links to near accidents arise from common initiating events and descriptive factors. Therefore, the occurrence of such events and DFs conveys essential information related to the probability of an extreme accident.

The methodology combines a complex BN model created with the events and DFs extracted from serious/major LOS incidents and the application of Information Theory to quantify the mutual information. These events and DFs are later used to establish exhaustive predictive scenarios to anticipate the occurrence of severe LOS or MAC.

This study illustrates how simple are inference methods to allow the exploration of information of simple operational errors to predict the likelihood of near accidents. Although there are other sophisticated approaches to the assessment of accident precursors, the added value of this information derives from the fact that near accidents frequently take place prior to major accidents. Therefore this method allows us to take advantage of an abundance of partially relevant data, which reflect operational issues and errors.

The processes, analyses, and modelling have demonstrated the detection of precursors for serious loss of separation incidents from simple reports and the construction of simple models for future incident prediction.

Within the present case study, a correlation between events and factors is set up and achieves predictive quality, which supports the identity of a set of events and factors that could occur with high probability in a new incident case.

In summary, the proposed methodology provides an in-depth diagnostic to serious loss of separation scenarios and predictive capacity for new incident analyses.

This methodology presents limitations as follows:

- Limitation on data source. The BN model is based on expert knowledge due to the quantitative limitation on incident data. Considering all events and factors extracted from reports could be occurring in other ATM occurrences not classified as incidents, this missing data might affect the accuracy of the information theory approach.
- Limitation on BN model. Uncertainty is inevitably presented in the BN model as other predictive models. To reduce its degree, the model needs to be updated continuously with new incident data.

Chapter 7.

7. HUNTING BLACK SWAN

'Contrary to social-science wisdom, almost no discovery, no technologies of note, came from design and planning—they were just Black Swans.'

— Nassim Nicholas Taleb, *The Black Swan: The impact of the highly improbable*

7.1. Introduction

The black swan theory describes that an event comes unexpectedly with a fatal effect and, after the fact, it is usually difficultly rationalized with the advantage of hindsight. This theory was promoted by Nassim Nicholas Taleb to explain the following three attributes in an event [16]:

1. **Rarity.** It lies outside the scope of acceptable expectations, nothing in the past can be consulted and provide convincingly supports to its possibility.
2. **Extreme impact.** It plays vastly roles with larger magnitude and consequences than regular occurrences.
3. **Retrospective predictability.** The cognitive biases as human nature blind people to acknowledge the massive role of the rare event, and concoct explanations of the occurrence after the fact of making their predictable.

This theory has received more attention in the risk management field of different sectors, which are interested in human and environment damage prevention related to hazardous industries and infrastructures. Aven has deepened the analysis in understanding the link between the theory and risk concept, and in consolidating the basis of meaning and characterisation of the risk [94]; Murphy and Conner have discussed lessons learned from black swan events in improving the design of chemical facilities and the limitations of existing risk assessment tools [95] [96]; Paté-Cornell has presented an engineering risk analysis considering epistemic and aleatory uncertainties and using all available information for decision making in order to proactive risk management [97].

The learning from small events has awakened special interest in industries as varied as nuclear power generation, oil and gas production, and air traffic management. It also has encouraged database applications for recording and classifying incident reports [98].

In this chapter, we attempt to hunt small failures occurred in air traffic management systems, applying the statistical classification to registered data. With the confusion matrix as auxiliary

support, we have adopted and modified the traditional risk assessment matrix to determine the risk of incident occurrences based on the likelihood of their precursors.

7.2. Objectives

During the previous analysis in chapter 6, due to the lack of complete data, a simplification in estimating the FPR value has been considered in each scenario. The FPR value assists in measuring the influence of one cause or a combination of multiple causes on operations that have not been notified as incidents. In the aviation industry, like other industries that require a demanding safety level, non-incident operations are dominant over incidents and accidents, although these rare events result in very severe or even catastrophic consequences, just compliance with characteristics of the black swan theory. Therefore, in this chapter, we intend to deepen the analysis in exploring how non-incident operations influence assessing the risk of producing incidents or accidents.

In order to archive this final goal, we attempt to follow a few steps in completing the following two landmarks:

- Demonstrate the importance of considering non-incident operations in estimating the risks of incidents or accidents. In non-incident operations, the data are difficult to be detected and collected; especially the complete frequency of occurrence of one cause, or a combination of several causes, is not measurable through real operations. It implies that not all cause-effect relationships that may occur in the aviation industry are known. Nevertheless, at the same time, we can question whether those data pertaining to non-incident operations are really necessary, or whether data resulting from incidents or accidents that have already occurred will be sufficient to predict the risks of new ones occurring. Therefore, we intend to analyse the impact of considering these non-incident operations in the risk analysis.
- Develop a method for assessing the risk of incidents or accidents with limited data. Following the first landmark, we intend to develop a method, which is capable of projecting the risk of new incidents or accidents into the traditional risk matrix, using the available data extracted from incident reports.

Contributing factors to incidents are detectable with associated frequencies of occurrence in incidents (TP value), or their future occurrences in incidents could be predicted by a BN model, while their contributions to non-incident operations (FP value) are unknown or the process of their detections should be supposed a complex task. In traditional risk matrix, probability defined in the column of frequency of occurrence identifies with the total probability of each contributing factor, or a combination of several factors. The risk matrix is suitable in the stage of system design and testing, in which the total frequency of occurrence of one factor could be estimated or calculated from testing results. On the contrary, for the same factor, its frequency of occurrence in real operations is only known partially from incident reports, and then the risk matrix is less practical in determining risk levels of contributing factors for preventing incidents. Therefore, traditional risk matrix would not be effective to assess the operational risk of these factors and it is necessary to be improved.

7.3. Briefing of Risk Matrix and Target Level of Safety

In air traffic management, every modification of training programs, change of the operational procedures, implementation of new equipment, or the update of software should be preceded by risk analysis in assessing whether a certain safety level will be maintained. Such risk analysis is required and defined by ICAO [39] as part of Safety Risk Management (SRM) whose objective is to assess the risk of identified hazards, develop and implement ad hoc mitigations to control the risk. For this purpose of risk assessment, a qualitative analysis tool like risk matrix is widely applied in aviation safety [99]. The risk matrix involves the severity, or the potential consequence, and the frequency of occurrence related to different undesirable risk factors, hence it can be also formulated as $RISK = Severity \times Frequency \text{ of Occurrence}$.

Figure 7-1 shows a standard risk assessment matrix defined by ICAO in its Safety Management Manual (SMM) [39], where the severity as well as the frequency of occurrences can be divided into five categories as follows:

- Severity: A – Catastrophic; B – Hazardous; C – Major; D – Minor; and E – Negligible or No Safety Effect.
- Frequency of occurrences: 1 – Extremely Improbable; 2 – Improbable; 3 – Remote; 4 – Occasional; and 5 – Frequent.

Severity Frequency		Catastrophic A	Hazardous B	Major C	Minor D	Negligible E
Frequent 5						
Occasional 4						
Remote 3						
Improbable 2						
Extremely Improbable 1						

Figure 7-1 – Risk matrix for safety occurrences (Source: ICAO Safety Management Manual [39])

The severity is a kind of classification of failure conditions, which represent the effect of one or more failures on the airplane and its occupants considering relevant adverse operational or environmental conditions [100]. In Table 7-1, effects associated with each category of failures conditions are summarized regarding EASA CS-25 [101].

Classification of Failure Conditions	No Safety Effect	Minor	Major	Hazardous	Catastrophic
Effect on Aeroplane	No effect on operational capabilities	Slight reduction in functional capabilities	Significant reduction in functional capabilities	Large reduction in functional capabilities	Normally with hull loss
Effect on Occupants excluding Flight Crew	Inconvenience	Physical discomfort	Physical distress, possible including injuries	Serious or fatal injury to a small number of passengers or cabin crew	Multiple fatalities
Effect on Flight Crew	No effect on flight crew	Slight increase in workload	Significant workload	Excessive workload impairs ability to perform tasks	Fatalities or incapacitation

Table 7-1 – Severity of the effects according to the classification of failure conditions (Source: EASA CS-25 [101])

Whilst, the frequency of occurrences measures the number of times that a safety consequence might occur and has the following meanings for its five categories:

- Extremely Improbable: Almost inconceivable or not occurred yet throughout the whole lifetime of the system.
- Improbable: Very few cases or unlikely to occur the failure.
- Remote: Unlikely to occur the failure.
- Occasional: Several similar cases or likely to occur the failure
- Frequent: A significant number of cases or likely occur many times the failure.

The safety risk should be assessed by the combination of both components into the risk matrix and it is possible to assign one tolerable safety level to the combined result. The tolerability criteria should be defined by the particular organization. Generally speaking, three levels of tolerability can be identified: intolerable or unacceptable area, tolerable or review area and acceptable area. For risk matrix illustrated in Figure 7-1, corresponding safety risk

tolerable levels are indicated by colours in Figure 7-2. If the risk assessment result lies on intolerable or unacceptable area, organization should take the following measures:

- Take measures to reduce the frequency of occurrences related to the particular risk;
- Take measures to reduce the severity of the identified hazard;
- If ad hoc mitigation is not possible, then the operation should be cancelled.

Figure 7-2 – Tolerability of safety risk (Source: ICAO Safety Management Manual [39])

Moving into the intolerable or unacceptable area suppose a very high risk in occurring incidents or accidents. Consequently, no design modifications or procedural changes should produce such results. In order to accurately determine the boundary of the intolerable area, several aviation agencies and organizations (international and national) have established quantitative and qualitative Target Level of Safety (TLS) associated with each severity. In other words, one TLS represents a maximum acceptable level of safety for determinate category of failure conditions.

In Europe, for aircraft manufacturing industry, EASA has released CS-25 [101] as compliance requirements for civil aeronautical manufacturers including their suppliers, in which a series of criteria have been established to achieve the TLS defined in both the system design and maintenance of large aeroplane. Derivate from the criteria defined in subpart F of AMC (Acceptable Means of Compliance) 25.1309 for system design and analysis [101], the allowable TLS of each severity is quantitatively and qualitatively defined in Table 7-2.

Classification of Failure Conditions	No Safety Effect	Minor	Major	Hazardous	Catastrophic
Allowable Qualitative Probability	No Probability Requirement	Probable	Remote	Extremely Remote	Extremely Improbable
Allowable Quantitative Probability	No Probability Requirement	Probability per FH on the order of $<10^{-3}$	Probability per FH on the order of $<10^{-5}$	Probability per FH on the order of $<10^{-7}$	Probability per FH on the order of $<10^{-9}$

Table 7-2 – Allowable probability associated with classification of failure conditions (Source: EASA CS-25 [101])

For ATM systems, EUROCONTROL has established the minima acceptable reference taking into account the TLS that have been undertaken by CS-25 [102]. The requirements defined in the Advisory Material Joint (AMJ) associated with CS 25.1309 are considered strict enough to fulfil the quantitative safety objectives expected in ATM systems. It should be highlighted that these criteria of CS are adopted and applied to determine the TLS in ATM environment, i.e. the goal of individual failure condition associated with catastrophic category is defined as 10^{-7} per working hour in an ATS unit. EUROCONTROL has invested a lot of resources in quantitatively determining the TLS of failure conditions with catastrophic results [103], i.e. the development of Collision Risk Models (CRMs) [104]. Nevertheless, for the remaining categories of occurrences, EUROCONTROL has delegated their determinations to the national levels as indicated in Table 7-3.

Classification of Severity	No Safety Effect	Minor	Major	Hazardous	Catastrophic
Maximum tolerable probability of ATM directly contribution	To be determined at national level	To be determined at national level	To be determined at national level	To be determined at national level	2.31×10^{-8} per flight or 1.55×10^{-8} per flight hour

Table 7-3 – Relationship between severity classification and risk classification for ATM specific occurrences (Source: ESARR 4 Risk Assessment and Mitigation in ATM [105])

In the practice, EUROCONTROL has developed and validated the Risk Analysis Tool (RAT) for ATM occurrence analysis [106] based on a combination of criteria, which assesses the risk of an occurrence that implies to both ground side (ATC centre) and air side (A/C and crew). As outcome of RAT, one risk matrix with highlighted risk level is provided to investigator in making decisions related to the investigation. Furthermore, although all notified occurrences should be investigated by the local authority, i.e. the State Investigation

Office in Spain, EUROCONTROL requires or highly desires that their interested parties use methodology like SOAM to investigate all accidents and occurrences identified as incidents with severity as serious, major and minor [60].

7.4. Methodology of Development

Figure 7-3 illustrates the methodology for proceeding with the analysis. As a starting point and step 1 of the methodology, the confusion matrix explained in chapter 6 is used to identify all parameters needed to complete this analysis. At chapter 6, during the last process of generating scenarios, the confusion matrix has been used to assess the accuracy of each scenario. This confusion matrix is a special two-dimensional contingency table, composed by 'actual value' and 'predicted outcome', which report the number of four cases: 'true positive', 'false negative', 'false positive' and 'true negative'.

Figure 7-3 – Methodology of risk analysis based on statistical classification and new risk matrix proposal

For coming analysis, it is convenient to convert each element within the confusion matrix into a frequency rate, calculated as the quotient between the element and the total number of operations during a determinate period. For example, we transform the number of “true positive” into the ratio $\frac{\text{True positive}}{\text{Number of operations}}$. Thus, each element of the confusion matrix can be modelled as a random variable, which uncertainty depends on the states of each cause, or combination of several causes (present/absent), in the results of the operations (incident/non-incident). That is, whether a cause has been present or not, in incidents and in normal operations or no incidents.

In this manner, as step 2, we can separate the set of total operations into two subsets according to the results of the operations. In other words, because of the characteristic of ‘*actual value*’, we have two subsets: one subset created by operations notified as incidents, and the other by non-incident operations. Each subset is affected by different uncertainties and responds to different statistical distributions. Consequently, all calculations carried out can be processed locally and decoupled between the two subsets.

After separating the subsets, in step 3, the risk analysis of each cause, or combination of several causes, can be split on these two subsets and transformed into the analysis of two local ratios: TPR and FPR. The value of TPR represents the probability of a cause, or combination of several causes, ending in an incident while, the value of FPR is the probability of the same cause, or the same combination of causes, not ending in an incident. The results of the analysis of these two ratios can be plotted into a diagram that will assist us in determining the risk of an incident as a function of TPR and FPR (step 4).

As a final step (step 5), the traditional risk matrix will be improved with the conclusions of the analyses, and the application of this new risk assessment matrix will be illustrated.

In addition, two boundary conditions for analysis should be considered during the analysis:

- i) within the aviation industry:

$$N^{\circ} \text{ Accidents} \ll N^{\circ} \text{ Incidents} \ll N^{\circ} \text{ Total air traffic operations};$$

- ii) the aviation industry has already reached a high and stable level of safety by complying with restricted TLS prescribed by different aviation authorities.

As an additional declaration, analysis hereof only refers to individual factor by wording simplification. The combination of several factors can be explained with the same reasoning.

7.4.1. Definition of mathematical parameters

As input, some mathematical parameters should be defined for following analysis. In chapter 6 it is explained that one factor or cause can be codified applying ADREP taxonomy and each taxon is considered as independent random variable.

Derivate from this observation, we can define a set of these independent random variables, which at the same time they are elements of an orthogonal base:

$$X \subset \mathbb{R}^n, X = \{factor_1, factor_2, \dots, factor_m \mid factor_1 \perp factor_2 \perp \dots \perp factor_m\}.$$

The X represents the set of all factors collected in ADREP database of Descriptive Factors with corresponding codes.

Meanwhile, other set of dependent random variables that represents all operations carried out in the air traffic management system should be defined as Y.

Moreover, the set Y of operations (Op) can be divided into subsets categorized in accidents (Op_{|A}), incidents (Op_{|I}) and non-incidents (Op_{|NoI}) as follows:

$$Y \subset \mathbb{R}^n, Y = \{Op_{|A}, Op_{|I}, Op_{|NoI} \mid Op_{|A} \cap Op_{|I} \cap Op_{|NoI} = \emptyset\}.$$

Within the subset of incident operations (Op_{|I}) three severity levels can be separated: A – ‘Serious incident’ (Op_{|I-A}), B – ‘Major incident’ (Op_{|I-B}), and C – ‘Significant incident’ (Op_{|I-C}). Despite of EUROCONTROL [20] has established five levels of severity, for analysis purpose, the occurrences notified as severity level D – ‘Not determined’ and E – ‘No safety effect’ are considered within the category of non-incidents.

Generally speaking, each factor in X can be presented in one or more operations of Y. Then, between sets X and Y one relationship can be defined:

$$\mathbb{R}^n \rightarrow \mathbb{R}^n: \forall i, X(factor_i) \rightarrow Y(Operation_j), \text{ or the same as Y is a function of X: } Y = f(X).$$

In the following, we will not consider those operations ending in accidents, due to the particular interest in which our research work has only been focused on ATM incident cases, and use the term of 'all operations' to refer both incident and non-incident operations.

When factors in present state, following associated subsets of operations can be identified:

- $\forall i, factor_i \in X_I \rightarrow Op|_I$, where X_I is the subset of factors that contributes to air traffic incident operations ($X_I \subset X$), meanwhile, its projection is the subset of incident operations $Op|_I$;
- $\forall i, factor_i \in X_{NoI} \rightarrow Op|_{NoI}$, where X_{NoI} is the subset of factors that contributes to air traffic non-incident operations ($X_{NoI} \subset X$), meanwhile, its projection is the subset of non-incident operations $Op|_{NoI}$;

Note that the relationship between subsets of X comply with next conditions:

- $X_I \cup X_{NoI} \subset X$, these two subsets only collect factors detected in ATM operations, while the sub X covers all descriptive factors defined in ADREP database independently of the detectability in real operations;
- $X_I \cap X_{NoI} \neq \emptyset$, the same factor that contributes to incident operations also can be detectable in non-incident operations.

Viewing the subsets projected in Y , a subset of all operations that is useful for forward analysis should be defined as follows:

$$Op = \{Op|_I, Op|_{NoI} \mid Op|_I \cap Op|_{NoI} = \emptyset\} \subset Y,$$

Regarding numbers associated with each subset of operations and used for statistical estimations, they are represented by the following parameters:

- For subset Op :
 N^0Op = total number of all operations;
- For subset $Op|_I$:
 $N^0Op|_I$ = total number of operations notified as incidents;
- For subset $Op|_{NoI}$:
 $N^0Op|_{NoI}$ = total number of non-incident operations;

- For subset Op in which $factor_i$ is in present:

$N^oOp|_f$ = number of times that $factor_i$ is presented in operations;

- For subset $Op|_I$ in which $factor_i$ is in present:

$N^oOp|_{I_f}$ = number of times that $factor_i$ is presented in incident operations;

- For subset $Op|_{NoI}$ in which $factor_i$ is in present:

$N^oOp|_{NoI_f}$ = number of times that $factor_i$ is presented in non-incident operations.

Additionally, complying with the condition $Op_I \cup Op_{NoI} = Op$, the relationship of numbers associated with subsets Op , $Op|_I$ and $Op|_{NoI}$ with $factor_i$ in present state can be established as $N^oOp|_f = N^oOp|_{I_f} + N^oOp|_{NoI_f}$.

Taking into account that these parameters are obtained from a normalized incident database as detailed in APPENDIX A – ATM INCIDENT DATABASE NORMALIZATION, i.e. if the codification chain shaped by Report_ID+Event_ID+DF_ID is repeated, it means that the same event and factor are detected twice in the same reported incident, then this incident should be counted as twice. Deriving from this normalization result, a new term related to number of incident operations with $factor_i$ in absent state can be established as below:

$N^oOp|_{I_NoI} = N^oOp|_I - N^oOp|_{I_f}$ = number of times that $factor_i$ is absent in incident operations.

7.4.2. Confusion matrix in terms of probability (step 1)

Hence, based on the relationship presented in Figure 7-4, the four components of the confusion matrix have the following mathematical interpretations, which each state of factors (present or absent) is associated with the operational result.

- TP: number of operations notified as incidents with the $factor_i \in X$ in present state,
 $TP = N^o Op|_{I_f}$;
- FN: number of operations notified as incidents with the $factor_i \in X$ in absent state,
 $FN = N^o Op|_{I_{NoI}}$;
- FP: number of operations not notified as incidents with the $factor_i \in X$ in present state.
 In this case, the $factor_i$ may be simply present in operations which have been not notified as occurrences for investigation, $FP = N^o Op|_{NoI_f}$;
- TN: number of operations not notified as incidents with the $factor_i \in X$ in absent state.
 In this case, all those operations are included without having notified as occurrences and with the factor in absent state, $TN = N^o Op|_{NoI} - N^o Op|_{NoI_f}$.

Figure 7-4 – Relationship between sets of variables

For estimating the presence of one factor in all operations, the parameter p can be defined as the probability of success, which one factor has been present in these operations

regardless of its contribution to incidents. Otherwise, if the same factor has been in absent, its probability defined by parameter $q = 1-p$.

Both parameters represent the uncertainty of a given factor in operations and are formulated as follows:

Equation 11:

$$p = \frac{N^o Op|_f}{N^o Op} = \frac{N^o Op|_{I_f} N^o Op|_I}{N^o Op|_I N^o Op} + \frac{N^o Op|_{NoI_f}}{N^o Op}$$

Equation 12:

$$\begin{aligned} q = 1 - p &= 1 - \left(\frac{N^o Op|_{I_f} N^o Op|_I}{N^o Op|_I N^o Op} + \frac{N^o Op|_{NoI_f}}{N^o Op} \right) \\ &= \frac{N^o Op|_I}{N^o Op} - \frac{N^o Op|_{I_f} N^o Op|_I}{N^o Op|_I N^o Op} + 1 - \frac{N^o Op|_I}{N^o Op} - \frac{N^o Op|_{NoI_f}}{N^o Op} \\ &= \left(1 - \frac{N^o Op|_{I_f}}{N^o Op|_I} \right) \frac{N^o Op|_I}{N^o Op} + \left(1 - \frac{N^o Op|_I + N^o Op|_{NoI_f}}{N^o Op} \right) \end{aligned}$$

The components of parameters p and q match the components of the confusion matrix estimated with respect to $N^o Op$. In other word, the components of the matrix can be transformed into probabilities, representing as follows the likelihood of the state of factors that contributes to all operations:

$$\text{Equation 13: } \frac{TP}{N^o Op} = \frac{N^o Op|_{I_f} N^o Op|_I}{N^o Op|_I N^o Op}$$

$$\text{Equation 14: } \frac{FN}{N^o Op} = \frac{N^o Op|_I - N^o Op|_{I_f}}{N^o Op} = \left(1 - \frac{N^o Op|_{I_f}}{N^o Op|_I} \right) \frac{N^o Op|_I}{N^o Op}$$

$$\text{Equation 15: } \frac{FP}{N^o Op} = \frac{N^o Op|_{NoI_f}}{N^o Op}$$

$$\text{Equation 16: } \frac{TN}{N^o Op} = \frac{N^o Op - N^o Op|_I - N^o Op|_{NoI_f}}{N^o Op} = \frac{N^o Op|_{NoI} - N^o Op|_{NoI_f}}{N^o Op}$$

In summary, Table 7-4 shows the confusion matrix defined in terms of probability.

	Actual Value – Positive	Actual Value – Negative
Predictive outcome – Positive	$\frac{TP}{N^o Op} = \frac{N^o Op _{I_f} N^o Op _I}{N^o Op _I N^o Op}$	$\frac{FP}{N^o Op} = \frac{N^o Op _{NoI_f}}{N^o Op}$
Predictive outcome – Negative	$\frac{FN}{N^o Op} = \left(1 - \frac{N^o Op _{I_f}}{N^o Op _I} \right) \frac{N^o Op _I}{N^o Op}$	$\frac{TN}{N^o Op} = \frac{N^o Op _{NoI} - N^o Op _{NoI_f}}{N^o Op}$

Table 7-4 – Confusion matrix in terms of frequency

7.4.3. Separation of subsets and their characterizations of uncertainties (step 2)

Table 7-4 indicates that the terms in the column of ‘Active Value – Positive’ are separated into two divisions:

- one is the proportion of the number of incident operations within the number of all operations ($\frac{N^o Op|_I}{N^o Op}$). This is a constant value and common on both outcomes.
- the other provides the information concerning how many factors have contributed to incidents within such operations ($\frac{N^o Op|_{I,f}}{N^o Op|_I}$ or $1 - \frac{N^o Op|_{I,f}}{N^o Op|_I}$). Both outcomes are variable depending on the contribution of each factor in incident operations.

From these two divisions, it can be observed that the uncertainty of these factors contributing to incidents can be reduced into an even smaller subset, the subset of incident operations ($Op|_I$), and their importance can be measured calculating the True Positive Rate as follows:

$$\text{Equation 17: } TPR = \frac{TP/N^o Op}{TP/N^o Op + FN/N^o Op} = \frac{N^o Op|_{I,f}}{N^o Op|_I}$$

From the column of ‘Active Value – Negative’, the contribution of each factor in non-incident operations is independent on the behaviour of the same factor in incident operations. It means that the uncertainty of these factors can be studied independently of what the same factors occur in incident operations. In a similar manner, the importance of these factors in contributing to non-incident operations can be measured estimating the False Positive Rate as follows:

$$\text{Equation 18: } FPR = \frac{FP/N^o Op}{FP/N^o Op + TN/N^o Op} = \frac{N^o Op|_{NoI,f}}{N^o Op|_{NoI}}$$

Since here, the analysis of the uncertainty of each factor in subset of incident operations and non-incident operations is separated into TPR analysis and FPR analysis as step 3a and 3b respectively.

7.4.4. True Positive Rate analysis (step 3a)

From the column of 'Actual Value – Positive', it can be observed that the ratio TP/FN features a local relationship $\frac{N^o Op|_{I,f}}{N^o Op|_I} / \left(1 - \frac{N^o Op|_{I,f}}{N^o Op|_I}\right)$, independent of the number of all operations. This ratio assesses the importance of the number of times that a factor is in present state in incident operations.

Applying this ratio to Equation 17, the following relationship is established with TPR:

$\frac{TP}{FN} = \frac{TPR}{1-TPR}$ and depicted in Figure 7-5 with logarithmic scale. Furthermore, the ratio TP/FN

can be analysed in depth in function of TPR as follows:

- If $0 \leq \frac{TP}{FN} < 1$, then $TP < FN$ and $TPR < 0.5$. Knowing the total number of incident operations, the number of incidents with the factor at present is less than half, and the probability of this factor in contributing to incident operations is less than 0.5. Consequently, this factor is not dominant in causing incidents.
- If $\frac{TP}{FN} \geq 1$, then $TP \geq FN$ and $TPR \geq 0.5$. Knowing the total number of incident operations, the number of incidents with the factor at present is more than half, and the probability of this factor in contributing to incident operations is more than 0.5. Consequently, this factor provides a high likelihood of causing incidents.

Figure 7-5 – TPR-vs-TP/FN

As shown in Figure 7-6, based on the discussion of TPR values, basically the probability of producing incidents can be identified in two areas. When $TPR \geq 0.5$, the factor that causes incidents is dominant over others and leads to an unsafe situation with high probability, then this indicates the risk of incidents due to this factor is higher and detectable. On the contrary, when $TPR < 0.5$, then the likelihood of causing incidents is lower and the unsafe situation caused by this factor is not as critical as the previous situation, since more than half of incident operations do not contain this factor.

Figure 7-6 – Probability area of causing incidents based on TPR values

7.4.5. False Positive Rate analysis (step 3b)

In this analysis, with the boundary condition $N^{\circ} \text{ Incidents} \ll N^{\circ} \text{ Total air traffic operations}$, we can observe that the FPR value nearly represents the frequency of occurrence of the factor in the set of total operations. Furthermore, depending on the nature of the factor, the analysis should be divided into two blocks:

BLOCK I: if the factor is known of contributing to incidents, the FPR value should be discussed in conjunction with the risk matrix like illustrated in Figure 7-1 for aircraft operational incidents.

BLOCK II: when the factor could not be detected because it has never been contributing to incidents historically. This case presents an uncertainty in determining the risk of causing future incidents.

In BLOCK I, only taking into account those factors have already been detected in previous incidents with $TPR \neq 0$ as initial condition. It means that the factor presents in non-incident operations being detected in incident operations. This kind of factors involves in safety effects on aircraft operations, and its allowable probability of acceptable safety level for minor incident severity should be less than 10^{-3} per flight hour (FH) as defined by EASA in Table 7-1. In spite of EUROCONTROL has established an equivalence between aircraft TLS measured by FH and ATC TLS measured by operative hour (OH) or working hour (WH) [102], i.e. the goal of 10^{-3} per FH is equivalent to 10^{-2} per OH in a ATS unit o single sector, this unit of measurement is even less suitable for measuring the probability of operational failure from ATM perspective. If one operation is considered as a series of clearance issued by one air traffic controller in a single control sector, to keep safely one aircraft from its entrance to the sector until its exit of the same, and the number of aircraft managed by the controller per operative or working hour is $O(10^1) \sim O(10^2)$ depending on the complexity of the sector, i.e. in European Network Operations Plan 2019-2024 [107], as one of the top airports with intense traffic daily, Madrid Barajas Airport has registered a global capacity of 100 operations per hour into Terminal Manoeuvring Area (TMA) with runways 36R / 36L for take-offs and 32R / 32L for landings. In other European airports, with less traffic intensity, the

average of operational capacity is in order of 40-60 operations per hour. Then the acceptable safety range for minor incidents would be $O(10^{-3}) \sim O(10^{-4})$ per operation. In addition, researchers like Heinrich [108] proposed a ratio of 1/10 between incidents and unreported occurrences based on collected data and, recently, Walker [109] postulated a ratio of 1/274 between serious incidents and occurrences in the UK aviation industry. In our estimation, considering conservatively the ratio proposed by Heinrich, the acceptable safety range of a factor presented in unreported occurrences, which are equivalent to those non-incident operations containing the factor, is $O(10^{-2}) \sim O(10^{-3})$ per operation, or the maximum acceptable safety level is less than 10^{-1} .

From this estimation result, two interpretations can be observed:

- First, the estimated frequency of what a factor contributes to non-incident operations is less than 10^{-1} , regarding the boundary condition i) defined in 7.4, the number of all operations and non-incident operations have the same order of magnitude, $N^oOp = N^oOp|_I + N^oOp|_{NoI} \approx N^oOp|_{NoI}$, then $\frac{FP}{N^oOp} = \frac{N^oOp|_{NoI.f}}{N^oOp} \approx \frac{N^oOp|_{NoI.f}}{N^oOp|_{NoI}} = FPR < 10^{-1}$.
- Second, the same factor can involve in all severity incidents manifesting through different mechanisms or failure conditions. Generally speaking, its probability of failure corresponding to each incident severity in design has complied with the TLS required by certification authorities, while its frequency of occurrence in operations shall be within an acceptable range and continuously under supervision of airworthiness authorities. However, it should not be discarded the situation that one factor presents with more frequency than the allowed and, specially, contributes to non-incident operations without being detectable. This situation is extremely improbable occurred due to the implementation of several barriers, which act as defences with objectives of mitigating failures before having a dangerous scenario. Such barriers also comply with tolerance of failure in design and can be external to systems like crew actions as part of abnormal procedures defined in QRH (Quick Reference Handbook) in case of continuing operations with system faults, or internal to systems like STCA or TCAS in

detecting the loss of separation automatically. When barriers had failed, based on principles of Reason [29], incidents or even accidents would be unavoidable to occur, and their contributing factors would be detectable.

In summary, as shown in Figure 7-7, probability areas of one factor presenting in non-incident operations can be identified based on the discussion with FPR values. The area of $FPR < 10^{-1}$ contains all maximum tolerable safety levels corresponding to incident severities, this border of $FPR = 0.1$ establishes the maximum acceptable safety level of the factor in all operational results not ending in occurrences. Beyond this border, in area with $FPR \geq 0.1$, we can find an extremely improbable situation that one factor occurs with more frequency of occurrence than barriers can tolerate and without being detectable as incidents.

Figure 7-7 – Probability area of presenting factors in non-incident operations based on FPR values

In BLOCK II, although factors have not been detected in incidents ($TPR = 0$), we can divide the analysis into two parts like in BLOCK I: $FPR < 0.1$ and $FPR \geq 0.1$. However, with $TPR = 0$, the reference for risk analysis is missed and the likelihood of factor in causing incidents

always lies on the line of $TPR = 0$. It implies that the risk analysis for this kind of factors is more complicated than can be carried out with allowable data. Additionally, one special case is detected when $FPR \sim O(10^{-1})$ the frequency of occurrence of the factor is high and no incident has occurred yet until it combines with other factors. For example, in a certain area of manoeuvre, pilots must arrive a WP_i to make a banking turn to change its heading, nevertheless, as usual pilots make the turn early by taking a 'shortcut'. For this error of manoeuvre only, it is possible that no aircraft would ever have an incident. Actually, in a scenario as illustrated in Figure 7-8, when the ATC based on its clearance coordinates the separation between two aircraft, while the pilot of one of them makes this 'shortcut' by operational custom without notification to ATC. Evidently, as the result of this manoeuvre, one incident of loss of separation is reported.

Figure 7-8 – Scenario of loss of separation due to a wrong manoeuvre by operational custom

The description of this factor coincides with the definition of latent error defined by Reason, which the adverse consequence of one error generated by agents may lie dormant within the system until it combines with other factors to breach defences of the system. This kind of hidden factors presents potential risk to incidents.

7.4.6. Risk analysis in function of TPR and FPR values (step 4)

Gathering conclusions of TPR analysis in 7.4.4 and FPR analysis in 7.4.5, a global interpretation of incident estimation associated with states of each contributing factor can be illustrated in Figure 7-9.

The area of $FPR \geq 0.1$ is independent of TPR values and the likelihood of one factor in participating in any operation is extremely improbable. Meanwhile, the other area of $FPR < 0.1$ can be divided into two zones, $TPR > 0.5$ and $TPR < 0.5$.

Figure 7-9 – Global view of TPR and FPR analyses

As particular interest, three corners within these two zones are observed:

- A: $TPR \rightarrow 1$ and $FPR \rightarrow 0$, the participation of factors in non-incident operations is near null, then all factors of this characteristic in present state not only make the likelihood of causing incidents higher, but also contribute only to incidents.
- B: $TPR \rightarrow 1$ and $FPR \rightarrow 0.1$, fully participation of factors in non-incident operations as well as in incident operations. This situation is more critical than A, $FPR \rightarrow 0.1$ means that the frequency of occurrence of a failure due to the contribution of this kind of factors is more than the acceptable requirements for any severity of incidents, i.e. the acceptable frequency of occurrence for incidents of severity minor is 10^{-3} per operation. Then, the presence of this kind of factors implies the possible failure or deficiency of barriers as explained in 7.4.5.
- C: $TPR \rightarrow 0$ and $FPR \rightarrow 0.1$, no participation of factors in incident operations, all factors in present state contribute to non-incident operations.

7.4.7. Proposal of the adapted risk assessment matrix (step 5)

In the previous analysis related to TPR and FPR values, we have already identified different areas of likelihood that an operation would end in incident depending on participations of the factor. In aviation this industry or other industries with high risk as well as safety requirements, for determinate category of failures certain frequency of occurrence is required by certification authorities and considered during the design process. Through the exhaustive process of certification and its due control, a high TLS in operations is kept in this kind of industry. Notwithstanding, failures occurred during operations are difficult to be controlled, especially whether they occur in operations that have not been classified as incidents or not notified for investigations. For this reason, we have estimated the probability of a factor that has been detected in incidents and could contribute to non-incident operations complying with an acceptable safety level. Under this estimated acceptable safety level, $FPR < 10^{-1}$, the impact assessment of one factor in present state on reported incidents can be reduced to the assessment of the number of times that the factor has been participating in reported incidents. As aforementioned that a failure in systems is a mode or mechanism of manifesting one or several factors (causes of the failure), then different ranges defined to frequency of occurrences, which associated with failures in systems, can be projected, as indicated in Table 7-5, to frequency of occurrences associated with the number of times that factors have been in present in reported incidents (TPR values).

Frequency of occurrences associated to failures	Frequency of occurrences associated to factors (TPR)
$10^{-4} \sim 10^{-3}$	1.0
$10^{-5} \sim 10^{-4}$	0.9
$10^{-6} \sim 10^{-5}$	0.8
$10^{-7} \sim 10^{-6}$	0.7
$10^{-8} \sim 10^{-7}$	0.6
$10^{-9} \sim 10^{-8}$	0.5
$<10^{-9}$	<0.5

Table 7-5 – Equivalence of frequency of occurrences between failures and factors

Therefore, the traditional risk matrix defined in Figure 7-1 can be modified adapting the new frequency of occurrences as follows:

Frequency of occurrences	TPR	Serious incident (A)	Mayor incident (B)	Minor incident (C)	Not safety effect (E)
Very frequent	[0.9, 1]	Unacceptable	Unacceptable	Unacceptable	Review
Frequent	[0.8, 0.9)	Unacceptable	Unacceptable	Review	Review
Occasional	[0.7, 0.8)	Unacceptable	Review	Review	Acceptable
Rare	[0.6, 0.7)	Review	Review	Acceptable	Acceptable
Extremely rare	[0.5, 0.6)	Review	Acceptable	Acceptable	Acceptable
	[0, 0.5)	Acceptable	Acceptable	Acceptable	Acceptable

Table 7-6 – Reduced risk assessment matrix

Table 7-6 presents the adapted risk matrix specially focused to risk analysis with operational data extracted from incident reports. The interpretation of risk levels in this adapted risk matrix is different respect to the traditional one, taking into account that each risk level is basically correlated with the fact of real safety barriers in preventing incidents:

- The unacceptable level means that safety barriers are deficient in preventing incidents, and the TLS for associated severity of incidents is not complied with requirements defined. In this case, the investigation must be continued in order to deepen the analysis of discovering reasons of the deficiency. Consistently, some actions like the redesign of safety barriers should be taken.
- The acceptable level means that although the factor contributes to incidents, the safety barriers are sufficient for fewer incidents to occur, in this manner, the system can be held at a stable TLS.
- At last, the review level is an intermediate term between unacceptable level and acceptable level. The safety barriers have not enough capacity to mitigate causes in preventing incidents, if they are not reviewed to improve their efficiencies.

7.4.8. Predictive risk assessment (step 5)

From this reduced risk matrix, two assessments are inferred on the incidents, knowing the range of factors detected in the actual incidents:

- i. Assessment of priori. The safety condition is determined with the factors already detected in the category of incident under assessment. When the frequency of occurrence of one factor belongs to high range, i.e. $TPR \in [0.9, 1]$, the status of contribution to incidents depends on which category of incident this factor has contributed to. For example, if one factor has been detected in incidents of severity A and its $TPR = 0.95$, then the contribution of this factor shows unacceptable level according to the reduced risk matrix; and some actions must be taken in reducing its probability of occurrence. Meanwhile, if the same factor also has been detected in incidents of severity B, but with $TPR = 0.6$, then the contribution of this factor shows that the associated safety barriers should be reviewed in reducing its probability of occurrence. Deriving from this example, when one factor contributes to two or more different incident severities, associated failures of systems could not be the same between incidents with different severities. This phenomenon will be analysed in more details in chapter 8.

As opposite case, when the frequency of occurrence of one factor belongs to low range, i.e. $TPR \in [0, 0.5)$, it means that the contribution of this factor to incidents is acceptable, and no revisions or actions related to safety barriers are required.

- ii. Assessment of posteriori. According to Heinrich's Pyramid Theory [108] [110], the risk of a higher severity incident (even accident) occurring is determined with the same factors already detected as precursors in the lower severity of incident. The risk evolution from low to high safety levels, as indicated in Figure 7-10, is determinate by the frequency of presenting the precursor in a particular severity of incidents. With the same previous example, the factor associated with incidents of severity A also preforms as a precursor to accident. This precursor is repeated with high frequency of

occurrence ($TPR = 0.95$) and its adapted risk assessment status is unacceptable. It means that the associated TLS with severity A is not achieved and the probability of producing an accident is high. Meanwhile, the frequency of occurrence of the same precursor is lower in incidents of severity B ($TPR = 0.6$), then the risk of producing an incident of severity A is moderate.

The same rationale in the opposite case, with $TPR \in [0, 0.5)$, there is no risk of evolution to a higher severity level.

Figure 7-10 – Risk path

Finally, we should not discard that one factor might repeat in the same incident and its TPR value is below 0.5, regardless of the incident category under study. Cases such as this must be detected and studied particularly, as there is a special interest in deepening the analysis and understanding what happened.

7.4.9. Algorithm

Considering all circumstances, we can design an algorithm to identify the contribution of critical factors, both individually and combinatorically, and introduce it into some incident database in order to detect the risk of incidents and accidents.

Algorithm 1 Risk Assessment

Initialization:

$x(i) \in X = \{factor_1, factor_2, \dots, factor_m\}$ #There is one or more factors for assessment.

$RM(a, b) := Risk_Assessment_Matrix$

Select case $Y = \{Accident, A, B, C, D, E, Non_Incident\}$

Case $y(j) \in \{Y \setminus \{Accident\}\}$

For $y_k(j) = 1$ to $N^oIncidents$ #The detection of repeated factors in the same incident.

If $x(i) = x(i + 1)$ **then**

Print 'The cause repeats in same incident'

End if

End for

$\forall x(i) \in y, TP(i) = \sum x(i)$

$$TPR(i) = \frac{TP(i)}{\sum y(j)}$$

if $RM(TPR(i), y(j)) \in \{Unacceptable, Review\}$ **then**

Print 'Warning: inefficient barriers performed & potential scenario for higher severity level detected!'

end if

End Select

7.5. Analysis and Discussion

As shown in Table 7-7, a total of 366 incidents of five categories have been recorded in Spanish airspace during four consecutive years, whilst the total number of air traffic operations carried out during this period is in order of 7 million as indicated in Table 5-1, then it is verified that $N^{\circ} \text{ Incidents} \ll N^{\circ} \text{ Total air traffic operations}$.

Incident Category	No. Incidents – Year 1	No. Incidents – Year 2	No. Incidents – Year 3	No. Incidents – Year 4	No. Incidents – Total
A	13	5	10	3	31
B	37	31	37	34	139
C	40	38	53	50	181
D	2	1	1	0	4
E	2	1	5	3	11
TOTAL	94	76	106	90	366

Table 7-7 – Incident status during four consecutive years

In the previous chapter, we have obtained the results of the most contributing factors in the incidents of severity A and B, then the formulations for each severity of incidents can be written as follows:

- For incidents of severity A.

$N^{\circ}Op|_{I-A_f}$ = number of times that $factor_i$ is presented in incident of severity A;

$N^{\circ}Op|_{NoI-A_f}$ = number of times that $factor_i$ is presented in operations not classified as incident of severity A;

$$N^{\circ}Op_f = N^{\circ}Op|_{I-A_f} + N^{\circ}Op|_{NoI-A_f};$$

$$\left. \frac{TP}{N^{\circ}Op} \right|_{I-A} = \frac{N^{\circ}Op|_{I-A_f}}{N^{\circ}Op|_{I-A}} \frac{N^{\circ}Op|_{I-A}}{N^{\circ}Op};$$

$$\left. \frac{FN}{N^{\circ}Op} \right|_{I-A} = \left(1 - \frac{N^{\circ}Op|_{I-A_f}}{N^{\circ}Op|_{I-A}} \right) \frac{N^{\circ}Op|_{I-A}}{N^{\circ}Op};$$

$$\left. \frac{FP}{N^{\circ}Op} \right|_{I-A} = \frac{N^{\circ}Op|_{NoI-A_f}}{N^{\circ}Op};$$

$$\left. \frac{TN}{N^{\circ}Op} \right|_{I-A} = \frac{N^{\circ}Op|_{NoI-A} - N^{\circ}Op|_{NoI-A_f}}{N^{\circ}Op};$$

$$TPR = \frac{TP/N^oOp}{TP/N^oOp+FN/N^oOp} \Big|_{I-A} = \frac{N^oOp|_{I-A.f}}{N^oOp|_{I-A}};$$

$$FPR = \frac{FP/N^oOp}{FP/N^oOp+TN/N^oOp} \Big|_{I-A} = \frac{N^oOp|_{NoI-A.f}}{N^oOp|_{NoI-A}}.$$

- For incidents of severity B.

$N^oOp|_{I-B.f}$ = number of times that $factor_i$ is presented in incident of severity B;

$N^oOp|_{NoI-B.f}$ = number of times that $factor_i$ is presented in operations not classified as incident of severity B;

$$N^oOp_f = N^oOp|_{I-B.f} + N^oOp|_{NoI-B.f};$$

$$\frac{TP}{N^oOp} \Big|_{I-B} = \frac{N^oOp|_{I-B.f}}{N^oOp|_{I-B}} \frac{N^oOp|_{I-B}}{N^oOp};$$

$$\frac{FN}{N^oOp} \Big|_{I-B} = \left(1 - \frac{N^oOp|_{I-B.f}}{N^oOp|_{I-B}}\right) \frac{N^oOp|_{I-B}}{N^oOp};$$

$$\frac{FP}{N^oOp} \Big|_{I-B} = \frac{N^oOp|_{NoI-B.f}}{N^oOp};$$

$$\frac{TN}{N^oOp} \Big|_{I-B} = \frac{N^oOp|_{NoI-B} - N^oOp|_{NoI-B.f}}{N^oOp};$$

$$TPR = \frac{TP/N^oOp}{TP/N^oOp+FN/N^oOp} \Big|_{I-B} = \frac{N^oOp|_{I-B.f}}{N^oOp|_{I-B}};$$

$$FPR = \frac{FP/N^oOp}{FP/N^oOp+TN/N^oOp} \Big|_{I-B} = \frac{N^oOp|_{NoI-B.f}}{N^oOp|_{NoI-B}}.$$

As results, Table 7-8 sorted by scenario description shows both assessment of priori and posteriori applying the risk assessment matrix.

Scenario - Severity	Scenario Description	TPR	Assm. Priori	Assm. Posteriori
6-B	12251500: Pilot's action in respect to ATC clearance	0.12	Acceptable	---
4-A	12252600: Pilot's air/ground/air communication	0.36	Acceptable	---
6-A	22060100: ATM's monitoring of A/C	0.36	Acceptable	---
4-B	22060100: ATM's monitoring of A/C	0.19	Acceptable	---
2-A	22080101: ATM's internal coordination of civil sectors in the same unit	0.43	Acceptable	---
8-B	22080203: ATM's coordination with an adjacent civil sector	0.11	Acceptable	---
9-B	22090000: ATM's traffic transfer	0.12	Acceptable	---

Scenario - Severity	Scenario Description	TPR	Assm. Priori	Assm. Posteriori
3-A	22120100: ATM's strategic planning for conflict detection	0.36	Acceptable	---
1-A	22120200: ATM's tactical execution of the conflict detection strategy	0.43	Acceptable	---
2-B	22130101: ATM's horizontal conflict resolution by radar vectoring/monitoring	0.15	Acceptable	---
7-B	23020700: ATC use of descent procedure	0.16	Acceptable	---
10-B	24010101: ATC use of phraseology	0.11	Acceptable	---
5-A	24010102: ATC use of readback/hearback error detection	0.36	Acceptable	---
3-B	24010102: ATC use of readback/hearback error detection	0.16	Acceptable	---
1-B	25050000: ATM service personnel operating procedures/instructions	0.30	Acceptable	---
5-B	27030000: ATC monitoring of sector traffic load	0.16	Acceptable	---
7-A	22120200+22060100: ATM's tactical execution of the conflict detection strategy & ATM's monitoring of A/C	0.64	Review	Accident
9-A	22120200+22060100+12252600: ATM's tactical execution of the conflict detection strategy & ATM's monitoring of A/C & Pilot's air/ground/air communication	0.79	Unacceptable	Accident
10-A	22120200+22060100+22120100: ATM's tactical execution of the conflict detection strategy & ATM's monitoring of A/C & ATM's strategic planning for conflict detection	0.79	Unacceptable	Accident
8-A	22120200+22060100+24010102: ATM's tactical execution of the conflict detection strategy & ATM's monitoring of A/C & ATC use of readback/hearback error detection	0.79	Unacceptable	Accident
11-A	22120200+22080101+22120100+12252600+24010102+22060100: ATM's tactical execution of the conflict detection strategy & ATM's internal coordination of civil sectors in the same unit & ATM's strategic planning for conflict detection & Pilot's air/ground/air communication & ATC use of readback/hearback error detection & ATM's monitoring of A/C	0.93	Unacceptable	Accident
11-B	25050000+23020700: ATM service personnel operating procedures/instructions & ATC use of descent procedure	0.47	Acceptable	---
12-B	25050000+23020700+24010102: ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection	0.59	Acceptable	---

Scenario - Severity	Scenario Description	TPR	Assm. Priori	Assm. Posteriori
13-B	25050000+23020700+24010102+22130101: ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection & ATM's horizontal conflict resolution by radar vectoring/monitoring	0.67	Review	Serious Incident
14-B	25050000+23020700+24010102+22130101+22060100 : ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection & ATM's horizontal conflict resolution by radar vectoring/monitoring & ATM's monitoring of A/C	0.74	Review	Serious Incident
15-B	25050000+23020700+24010102+22130101+22060100 +22090000: ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection & ATM's horizontal conflict resolution by radar vectoring/monitoring & ATM's monitoring of A/C & ATM's traffic transfer	0.81	Unacceptable	Serious Incident
16-B	25050000+23020700+24010102+22130101+22060100 +22090000+24010101: ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection & ATM's horizontal conflict resolution by radar vectoring/monitoring & ATM's monitoring of A/C & ATM's traffic transfer & ATC use of phraseology	0.86	Unacceptable	Serious Incident
17-B	25050000+23020700+24010102+22130101+22060100 +22090000+24010101+12251500: ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection & ATM's horizontal conflict resolution by radar vectoring/monitoring & ATM's monitoring of A/C & ATM's traffic transfer & ATC use of phraseology & Pilot's action in respect to ATC clearance	0.90	Unacceptable	Serious Incident
18-B	25050000+23020700+24010102+22130101+22060100 +22090000+24010101+12251500+27030000: ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection & ATM's horizontal conflict resolution by radar vectoring/monitoring & ATM's monitoring of A/C & ATM's traffic transfer & ATC use of phraseology & Pilot's action in respect to ATC clearance & ATC monitoring of sector traffic load	0.93	Unacceptable	Serious Incident
19-B	25050000+23020700+24010102+22130101+22060100 +22090000+24010101+12251500+27030000+22080203: ATM service personnel operating procedures/instructions & ATC use of descent procedure & ATC use of readback/hearback error detection & ATM's horizontal conflict resolution by radar vectoring/monitoring & ATM's monitoring of A/C & ATM's traffic transfer & ATC use of phraseology & Pilot's action in respect to ATC clearance & ATC monitoring of sector traffic load & ATM's coordination with an adjacent civil sector	0.96	Unacceptable	Serious Incident

Table 7-8 – Risk assessment priori and posteriori of potential scenarios

According to the assessment results provided in Table 7-8, the scenarios created by individual factors do not yield risk with unacceptable level, and not all scenarios created by the combination of factors provide unsafety situation, i.e. the scenario '*25050000+23020700: ATM service personnel operating procedures/instructions & ATC use of descent procedure*', its risk level is acceptable.

Another particular interest, two factors have been detected to be involved in both categories of incidents: '*22060100: ATM's monitoring of A/C*' and '*24010102: ATC use of readback/hearback error detection*'. Despite fact that individual contributions do not create risk potential scenarios, their combination provides $TPR > 0.5$ if it was occurred in severity A incidents and $TPR < 0.5$ in severity B. In other words, the scenario created only by these two factors produces a possible proper incident of severity A and, at the same time, it is potential candidate to accident. In any case, this kind of factors chained in two continuous levels of severity deserves a qualitative study separately applying Heinrich's Pyramid Theory.

7.6. Conclusion

The development of this methodology builds on an already constructed incident model that allows the identification of the most contributing causes, i.e. BN model. The information theory is applied in depth to reduce uncertain data, in this manner only incident data are available to assess the estimated risk in conjunction with the risk assessment matrix, thus potentially simplifying the complexity of the problem. Additionally, during the analysis of FPR values, we have observed that the existence of hidden factors should be considered. However, despite having identified this problem, the deepening of the analysis in the search for a method that enables to assess the risk of these hidden factors is outside the scope of this dissertation.

Notwithstanding, without discarding that this methodology is only suitable for systems in which the number of incidents is much lower than the total number of operations performed. These systems are quite stable with a safety level already reached in order to consider the boundary conditions proposed during the aforementioned development.

Black Swan is a phenomenon of primordial importance in industries that already have high safety levels and require continuous improvements. In the aviation industry or other similar industries where incidents and accidents occur less frequently, but their consequences are serious, this method not only allows a qualitative and efficient detection of the risk to produce incidents, but also assess the risk of progressing the potential scenarios to higher severity levels.

Chapter 8.

8. HEINRICH PYRAMID THEORY

Nullum magnum ingenium sine mixtura dementiae fuit

(There is no great genius without a tincture of madness)

8.1. Introduction

Heinrich's Pyramid Theory is another influential theory such as the Swiss chess model (SCM) of Reason [38] in safety science. This theory suggests that minimizing the number of incidents with lower levels of severities leads to reducing the number of high severity events, including accidents [108]. According to this theory, a large number of incidents with low consequences, if untreated, would potentially lead to few occurrences with high consequences [110]. Moreover, a progressive increase in minor incidents would lead to a major accident. Whilst some researchers disagree with Heinrich by stating that accidents are caused by poor management systems as the main reason and not by human actions [111] and provide criticism related to the lack of qualitative representation of this theory [112], the pyramid theory is still widely applied for safety management in different sectors. Kyriakidis et. al. [113] have deepened this theory in improving accident precursor monitoring program of railway safety; Golovina et. al. [114] have designed an algorithm based on this theory for preventative hazard recognition and control process related to construction safety. Marshall et. al. [115] have turned to statistical methods to confirm Heinrich's theory in occupational accidents. For industrial process analysis, Prem et. al. [116] have generated safety pyramids based on historical databases of chemical industrial accidents and compared them with Heinrich's pyramid to understand incident occurrence trends.

Particularly, in the aviation sector, Walker [109] has established a risk pyramid with quantitative relation between occurrences, incidents, and accidents based on data registered in black boxes with the purpose of improving flight data monitoring system. Majumdar et. al. [117] have applied this theory directly to develop safety indicators using the data of LOS incidents registered in airspaces of New Zealand and the United Kingdom; however, unlike the quantitative relation considered in Heinrich's pyramid, Nazeri and Lance [118] have applied this theory in looking for a qualitative relation between accidents and incidents through their underlying factors.

Most of these researchers have used big data sources to demonstrate the validity of Heinrich's pyramid theory [115], and thus show the proportion between occurrences with different levels of severity [118]. Based on this theory, they have established a quantitative relationship between occurrences with their source data. Even Heinrich in [108] postulated that, for each accident with major injury, there were 29 accidents with minor injuries and 300 accidents without injuries. However, both Heinrich and these researchers have not examined the mode of connection or contribution of underlying causes to occurrences with different levels of severity. Such a qualitative relationship is no less important than the quantitative one and it might support us in understanding the stream of causes from a low to a high level of severity.

From this perspective, statistical models that can establish the qualitative relationship between different levels of the pyramid will be advantageous in comprehending the proximity to fatalities [116]. In the previous chapters, we followed a series of steps in extracting serious incident data (chapter 4) for BN construction (chapter 5) as well as searching possible scenarios where influential causes contributed to this category of accidents (chapter 6). Thus, one qualitative study related to the connections should be necessary and support us to detect the behaviour of each factor in different categories of incidents, even its associated events. For this reason, we employed the use of convolution operator, one mathematical operator, in filtering [119] and amplifying the information [120] contained in this kind of factors.

8.2. Objectives

In chapter 6, results indicated that some causes contribute to different categories of incidents. Their combinations provide potential scenarios leading to an accident in one category of incidents, but not in another. Derivate from this result, we can observe that common factors can be identified connecting different categories of incidents with different contributions. Therefore, the analysis should be deepened in the following points:

- Apply Heinrich's Pyramid Theory in studying air traffic management incidents. Based on the results in chapter 6, it is deduced that a relationship might be established between factors and categories of incidents; such relationship approximates that described by Heinrich's Pyramid Theory concerning causes and levels of severity. In addition, to check whether this theory explains the results obtained in previous papers, we are also interested in knowing if one relationship would be established between causes and different categories of incidents occurring within the ATM system.
- Detect correlations between factors and different levels of incident severity. If factors connect between different levels, we need to know what correlation is established between factors and incident severity levels. In this manner, it is possible to study the behaviour of each factor and its mode of contribution or stream within these incidents.

8.3. Methodology

Steps of the methodology that we have followed during this research work are indicated in Figure 8-1. Even though steps 1 thru 6 have been already exhaustively defined in the chapter 6, they are summarized below in keeping the contextual connection.

The initial phase (steps 1 thru 4) aims to detect causes and failures contributing to LOS serious and major incidents. Data collected from these incident reports are identified as factors and events, which are also denominated as precursors to future accidents. These factors and events can be extracted and codified by standardized methodologies [32] [60] [121] and taxonomies [64], which have been applied in this process. Factors based on taxonomy can be divided into two groups: descriptive factor (DF) and explanatory factor (EF). Both groups of factors represent causes of failures, meanwhile, events are identified as failures of the system.

In the second phase (step 5) based on the established correlation between factors and events, a BN model can be developed and validated. Moreover, a quantitative cause–effect map can be depicted through the BN model (factors as children nodes and events as parent nodes) and used to recreate scenarios of serious and major LOS incidents. Within the BN model, the likelihoods of factors and events, as well as their strength of the connections, are estimated based on the number of analysed incident reports and collected in the conditional probability table (CPT) [79].

During the third phase (step 6) the information theory developed from entropy principals is applied to identify the most correlated precursors of serious and major LOS incidents. The mutual information concept is used in quantifying the contribution of causes to these two incident severities and formulated as Equation 7.

Figure 8-1 – Methodology of convolution operator application to Heinrich pyramid theory in detecting common causes between incident severities.

During the last phase, Heinrich's Pyramid Theory is considered in analysing precursors. Regarding Heinrich's Pyramid Theory, factors that contribute to critical incidents, or with a higher severity level, are also present in less critical incidents or lower levels of severity. The application of this theory affords the identification of factors that have been involved in the incidents of severity A and B, and reveal their modes of participation in the incidents. However, this theory provides less qualitative correlation, which indicates the mode of contributing and the connection of these factors within two proximate severities. Consequently, without knowing the detail of this correlation, suitable design of barriers that allow the effective mitigation of events would not be carried out. Therefore, we can deepen the analysis by identifying the factors that chain between severity levels (concatenated factors), and their connectivity behaviours within different categories of incidents caused by them. Hence, Equation 19 of convolution for discrete sets [122] is applied to two sets of incidents with different severities, thereby filtering and amplifying information on factors common to both categories of incidents (step 7).

$$\text{Equation 19: } I[k]_f * I[k]_g = \sum_l I[l]_f I[k-l]_g$$

where I_f and I_g are functions of mutual information of two sets of incidents with different and proximate severities. Additionally, according to the commutative property of convolution, $I_f * I_g = I_g * I_f$, the convolution from one set to another presents a symmetrical

interpretation. Developing Equation 19, one generic convolution matrix related to the status of mutual information of a factor in two close severities is created as indicated in Table 8-1 (step 8).

$I(1,1) _f \cdot I(1,1) _g$	$I(1,1) _f \cdot I(1,2) _g$ $+I(1,2) _f \cdot I(1,1) _g$	$I(1,2) _f \cdot I(1,2) _g$
$I(1,1) _f \cdot I(2,1) _g$ $+I(2,1) _f \cdot I(1,1) _g$	$I(1,1) _f \cdot I(2,2) _g + I(1,2) _f \cdot I(2,1) _g$ $+I(2,1) _f \cdot I(1,2) _g + I(2,2) _f \cdot I(1,1) _g$	$I(1,2) _f \cdot I(2,2) _g$ $+I(2,2) _f \cdot I(1,2) _g$
$I(2,1) _f \cdot I(2,1) _g$	$I(2,1) _f \cdot I(2,2) _g$ $+I(2,2) _f \cdot I(2,1) _g$	$I(2,2) _f \cdot I(2,2) _g$

Table 8-1 – Mutual information matrix for two proximate categories of incidents

Three associated situations of incidents are shown independently of the factor states (columns of the matrix):

- i. Both categories of incidents are in present states;
- ii. One of them is in the present state and the other one in the absent state;
- iii. Neither of them is in the present state.

The other three situations associated with the status of the factor are shown independently of the incident states (rows of the matrix):

- i. The factor belongs to both incident categories;
- ii. The factor only belongs to one of both incident categories;
- iii. The factor is from neither of both incident categories.

Finally, the total number of mutual information that both severities of incidents share by this factor is the sum (I) of these nine components in the convolution matrix. Depending on the result of this sum of mutual information, three cases related to the participation and the behaviour of factors in different incident severities can be discussed (step 9).

8.4. Results of Application

As input data, a set of serious and major LOS incidents occurred between commercial aircraft in the Spanish airspace during four consecutive years has been considered (step 1). The analysis of incident reports provides causal–effect paths leading to serious and major LOS (step 2), and precursors that are extracted and attributed to events and factors (step 3). Finally, these precursors are registered in a database as mathematical parameters (step 4). Figure 8-2 illustrates the proposed BN model in this research work. The model is a transformation from the result in chapter 6 with Heinrich's pyramid theory in consideration (step 5). The CPT of correlation between factors and events is the same in Table 6-1 and Table 6-2. In addition, ADREP codifications of events and descriptive factors implicated in this research work are listed in Appendix B.

Events and factors have been divided into five groups within this BN model:

- Group 1, children nodes on the air side, group of DFs related to A/C or flight crew.
- Group 2, children nodes of connection, group of DFs related to A/C or flight crew – ATM.
- Group 3, children nodes on the ground side, groups of DFs related to ATM.
- Group 4, parent nodes on the air side, group of events related to A/C or flight crew.
- Group 5, parent nodes on the ground side, group of events related to ATM.

The difference with respect to results represented in chapter 6 is that, after considering Heinrich's pyramid theory, events and factors can be organized and presented in such manner that they are associated with different levels of severity. In other words, with Figure 8-2, events and factors in severity A level are common to both incident severities. Meanwhile, events and factors in severity B level are singular from major incidents.

Figure 8-2 – Heinrich's pyramid Bayesian Network (BN) model for loss of separation (LOS) serious and major incidents in commercial aviation

From the BN model, the likelihood of each factor is used to estimate its mutual information. Applying Equation 7, we obtain two matrices of mutual information of LOS incidents with severity A and B, $\mathcal{M}(I)|_A$ and $\mathcal{M}(I)|_B$ (step 6) and the sum of their components in each matrix is the mutual information for a particular DF in our validated BN model, $I_A(DF_i)$ and $I_B(DF_i)$. Applying Equation 19 to both matrices: $\mathcal{M}(I)|_A \otimes \mathcal{M}(I)|_B = \mathcal{M}(I)|_B \otimes \mathcal{M}(I)|_A$ (step 7). Then the convolution matrix of each DF is calculated and shown in Table 8-2 (step 8).

$I(1,1) _A \cdot I(1,1) _B$	$I(1,1) _A \cdot I(1,2) _B$ $+ I(1,2) _A \cdot I(1,1) _B$	$I(1,2) _A \cdot I(1,2) _B$
$I(1,1) _A \cdot I(2,1) _B$ $+ I(2,1) _A \cdot I(1,1) _B$	$I(1,1) _A \cdot I(2,2) _B + I(1,2) _A \cdot I(2,1) _B$ $+ I(2,1) _A \cdot I(1,2) _B + I(2,2) _A \cdot I(1,1) _B$	$I(1,2) _A \cdot I(2,2) _B$ $+ I(2,2) _A \cdot I(1,2) _B$
$I(2,1) _A \cdot I(2,1) _B$	$I(2,1) _A \cdot I(2,2) _B$ $+ I(2,2) _A \cdot I(2,1) _B$	$I(2,2) _A \cdot I(2,2) _B$

Table 8-2 – Mutual information matrix for incidents of severity A and B

Moreover, the sum of its components, $I(Z, Y)|_{A \cap B} = \sum_{i,j} I(i, j)|_{A \cap B}$, is the mutual information of each DF in both severity A and B ($I_{A \cap B}$).

As a result, we have three vectors of mutual information for all DFs contributed in the validated BN model: $I_A(DF_1, DF_2, \dots, DF_n)$, $I_B(DF_1, DF_2, \dots, DF_n)$ and $I_{A \cap B}(DF_1, DF_2, \dots, DF_n)$. For facilitating the analysis, each vector is normalized with respect to the sum of all its components.

Regarding the estimated mutual information that measures the participation of common factors in both categories of incidents, the factors can be identified within the following three groups (step 9):

Group 9.1. As shown in Figure 8-3, all factors have $I_{A \cap B} = 0$. It means that no mutual information is shared between both severities by the same factor, and these kinds of factors with such characteristics are listed in Table 8-3 and belong to one category of incidents only. According to Heinrich's pyramid theory, these kinds of factors should be specific to incidents with low severity level, i.e., severity B in this case.

DF ID	DF Belong to Severity B
11222000	Speed-attitude correction system

DF ID	DF Belong to Severity B
12210500	Pilot's perception of visual/oral warning
12210900	Pilot's obstacle clearance judgement
12230900	Pilot's operation of emergency brakes
12240600	The rate of descent of the aircraft
12240700	The flying speed of the aircraft
12251400	Pilot's action in respect to instruction
12251500	Pilot's action in respect to ATC clearance
12252200	Pilot's action in respect to standard operating procedure
21010900	Headsets
21020103	ATM's use of the instrument landing system
21030401	ATM's use of secondary area radar
21040200	ATM's information data system
22050100	A/C performance differences
22060200	ATM's monitoring of frequencies
22080201	ATM's coordination with an adjacent civil unit
22080203	ATM's coordination with an adjacent civil sector
22090000	ATM's traffic transfer
22110200	ATM's updating of a flight plan
22130200	ATM's vertical conflict resolution
22130300	ATM's conflict resolution by planned controller action
23010200	AWY/Route approach procedure
23010201	Surveillance radar element of a precision approach radar system approach
23010700	Emergency procedure
23020300	ATC use of approach procedure
23020500	ATC use of climb procedure
23020600	ATC use of departure procedure
23020700	ATC use of descent procedure
23020800	ATC use of emergency procedure
23021100	ATC use of holding procedure
24010105	ATC call-sign confusion
24010106	ATC transfer of communication
24010304	Information input error in the ATC operations
24010605	ATC provision of airborne proximity warning
26070000	ATM handling of A/C unusual/emergency situation
27010300	ATC rostering/sector opening in relation to expected traffic
27060100	ATC assistance to the ATC in recovering control of traffic
52010200	Instrument meteorological conditions
52020500	Crosswind
52021200	Turbulence in cloud
52031600	Thunderstorm

Table 8-3 – Associated DFs of severity B with I = 0

Figure 8-3 – Descriptive factors (DFs) with $I_A \cap B = 0$

DF ID	DF due to the Boundary Conditions
22080303	Revision of ATM's coordination procedures
22100700	Familiarization with traffic during the hand-over/take-over
24010107	ATC requirement for the acknowledgement of information by the Pilot
24010704	ATC provision of a minimum safe flight level/altitude/height/sector altitude
24010705	ATC provision of delay related information
27050200	Factors relating coordination with ATFM
41100300	Runway obstruction

Table 8-4 – Associated DFs of severity A with $I = 0$

However, there are ones listed in Table 8-4 that belong to incidents of severity A, the high severity level. This singularity exists when the study is limited by the established boundary conditions for our case study:

- Incident severity: serious and major incidents are considered;
- Incident category: LOS or SMI;
- Type of flight: limited only to commercial aircraft involved in the incident scenario;

- Operating phase: none of the involved aircraft were operating at the final approach phase or before achieving the second segment of the take-off, as indicated in Figure 8-4.

Figure 8-4 – Boundary conditions of the case study

If these boundary conditions are removed, i.e., extending cases studies considering other types of flight like incidents occurred between military and civil aircraft, these factors would be present in incidents of severity B, lower level of severity, regarding Heinrich's Pyramid Theory.

Group 9.2. As shown in Figure 8-5, all factors listed in Table 8-5 have $I_{A \cap B} \rightarrow 0$. The mutual information shared by factors within all incidents of severity A and B are close to zero. It means that these factors provide a weak connection to both severity levels.

DF ID	DF Belong to Severity A or B Separately
12232800	Pilot's operation of communication equipment
22080103	ATM's internal coordination of military sectors in the same unit
22100600	Briefing for the hand-over/take-over
23020400	ATC use of clearance procedure
24010103	Blocked communication
24010301	ATC requirement for the acknowledgement of information by the ATCO
24010703	ATC provision of flight information
52020400	Tailwind
52031400	Cloud amount restricting visibility

Table 8-5 – Associated DFs of severity A and B with $I \rightarrow 0$

Figure 8-5 – DFs with $10^{-10} < I < 10^{-3}$ ($I \rightarrow 0$)

According to the property of Kullback-Leibler divergence (KLD) [123][124], these factors contribute to both severities separately. In other words, they are in present either in severity A incidents or in severity B incidents. This result, checked together with the BN model, shows that all factors are linked to two independent joints of events, such that each joint belongs to one specific category of incidents without intersection with others. For example, if the factor '24010103 Blocked communication' is in the present state, then events '2020300 Communication between pilot and ANS' and '1230000 Communication systems' could be affected. However, the event '2020300 Communication between pilot and ANS' belongs to severity A incidents, meanwhile the event '1230000 Communication systems' belongs to severity B incidents only.

Group 9.3. As shown in Figure 8-6 all factors listed in Table 8-6 contribute to both categories of incidents through common events.

DF ID	DF Shared in Severity A and B
12251800	Pilot's radiotelephony phraseology
12252600	Pilot's air/ground/air communication
22060100	ATM's monitoring of A/C

DF ID	DF Shared in Severity A and B
22080101	ATM's internal coordination of civil sectors in the same unit
22100300	Airspace during the hand-over/take-over
22120100	ATM's strategic planning for conflict detection
22120200	ATM's tactical execution of the conflict detection strategy
22130101	ATM's horizontal conflict resolution by radar vectoring/monitoring
23010300	Clearance procedure
24010101	ATC use of phraseology
24010102	ATC use of readback/hearback error detection
24010604	ATC provision of a short term conflict alert (STCA) warning
25050000	ATM service personnel operating procedures/instructions
27030000	ATC monitoring of sector traffic load

Table 8-6 – Associated DFs of severity A and B with $I > 0$ Figure 8-6 – DFs with $I > 10^{-3}$

These events leading to either of the two incident categories are manifested, whilst the factors are in the present state. For example, when the factor '24010102 ATC use of readback/hearback error detection' is in the present state, then the events in Table 8-7 could be affected. Moreover, the mutual information of this factor is higher than others due to its stronger connection to both severities through the event '2020300 Communication between pilot and ANS'.

Severity	Event ID	Events Associated to DF 24010102
A&B	2020300	Communication between pilot and ANS
B	2020513	Clearance deviation - special procedure
B	2020517	Deviation from clearance - assigned flight level
A	4010100	ANS operational communications
B	4010400	ANS conflict detection and resolution

Table 8-7 – Associated events in severity A and B when DF 24010102 in present state

In summary, contribution paths of causes to incidents are performed through events in three paths as indicated in Figure 8-7:

- Causes only belong to severity B incidents contribute exclusively to this category of incidents, then the mutual information of both categories of incidents is zero ($I_{A \cap B} = 0$);
- Common causes belong to incidents of severity A and B can contribute to each category of incidents through the same mechanisms or events. In this case, the mutual information of both categories of incidents is different to zero ($I_{A \cap B} \neq 0$);
- Common causes belong to incidents of severity A and B and contribute to different categories of incidents through different mechanisms or events. In this case, the mutual information of both categories of incidents tends to zero ($I_{A \cap B} \rightarrow 0$).

Figure 8-7 – Contribution path of causes to incidents

8.5. ANN Model Proposal from the Analysis Result

In addition, based on the analysis results and this reorganization of the BN model, connections between different groups of events and factors provide other interpretations with a tendency to possible applications of neuronal networks. As indicated in Figure 8-8, this simple Multilayer Perceptrons (MLP) neuronal network consists of three layers:

- Input layer, i : shaped by classified groups of factors (x_i);
- Hidden layer, j : performed by events groups (y_j);
- Output layer, k : provided by results of incident prediction (O_k).

Therefore, the general MLP equation for each layer can be formulated as follows:

Equation 20: $x_i = P(DF_i)$

Equation 21: $y_j = \sum w_{ij}I_i + b_j$, being $I_i = f(x_i)$

Equation 22: $O_k = \sum w_{jk}y_j + b_k$

In Equation 21 and Equation 22, w_{ij} and w_{jk} are weight parameters after the convolution for estimated mutual information, depending on the participation of the DF in different incident categories, i.e. if one DF belongs to severity A incident only, then the w_{ij} for events of severity B incidents are null ($w_{ij} = 0$); meanwhile x_i (input layer) is the estimated likelihood of each DF in the BN model, y_j (hidden layer) and O_k (output layer) correspond to the mutual information in function of x_i . Note that b_i and b_j are bias for additional weight adjustments in neuronal networks.

The method of applying Bayesian Network to neuronal networks training became popular, researchers like Huang et. al [125] al applied this method for foreign exchange rates forecasting, Abdulhai et. al [126] used it for freeway incident detection, and Gupta and Schumann [127] implemented it for improving flight control system.

Unlike other researchers that have used Bayesian Network as a data filter for neuronal network training, through this analysis we attempt to show a possible construction of a Bayesian-driven neuronal network model. In this manner, we could have a neural network with its hidden layer controlled. When a factor is located in a possible occurrence, we would

know with which event group this factor would be associated and to which incident category it would be contributed.

Figure 8-8 – Convolutional neuronal network

8.6. Conclusion

In this analysis, Heinrich's Pyramid Theory has been considered as the main approach that allowed the detection of common factors within different levels of severity as well as their relationship. According to this theory, causes detected at high levels of severity are always found at low levels; therefore, these causes are identified as concatenated factors, which contribute to incidents through their pertinent events.

Moreover, we have explored this theory in depth through the analysis of mutual information between both severity levels, and introduced it in refining the contribution of factors to different categories of incidents.

For deepening the analysis, we have selected all LOS incidents of severity A and B that occurred in the Spanish airspace during four consecutive years. The selection of these two joints of incidents has been specified by defined boundary conditions. The equation of convolution for discrete sets is applied in estimating qualitatively the mutual information between these incident joints, and hence the behaviour of factors and their modes of contribution within incidents depending on values of mutual information.

8.6.1. Benefits of the application

The application of this methodology illustrates how the simple application of the convolution operator to Heinrich's pyramid theory makes clearer the contribution of causes in incidents occurred due to operational failures. The added value of this technique allows us to detect contributing paths of causes leading to incidents.

Additionally, with the filtration of mutual information calculated within different incident severities, the correlation between causes, failures and incident categories are identified more clearly. We can observe that some common factors (causes) provide common events (failures) and belong to both incident severities. However, from these events, different paths have been separated into two categories of incidents, i.e., with determinate factors, some events only contribute to severity A or B incidents and others contribute to both categories of incidents. In other words, the same causes detected in different categories of incidents can

provide different streams through various failures. Consequently, although we know the causes of operational failures, one solution focused on avoiding the failures does not prevent incidents occurring. Indeed, this conclusion could guide us to reassess the design of barriers in avoiding the recurrence of causes.

8.6.2. Limitations of the application

The proposed methodology presents limitations as follows:

- Computational limitation: Although one neuronal network model based on the BN approach can be proposed, the number of cases for network learning is limited due to serious and major incidents occurring rarely.
- Data limitation: Causes and failures of serious and major incidents are known only from incident reports, or their frequencies of occurrence are partially known. Therefore, data related to their contributions to non-incident operations or incidents with less severity, i.e., minor incidents (severity C), are missed and, consequently, the accuracy of the information theory approach is compromised due to data limitations.
- BN model limitation: the model requires continuous updating of data to provide a higher level of reliability and reduce the degree of uncertainty.

8.6.3. Future work

- The proposed Bayesian-driven neuronal network model is limited to a conceptual design currently. Thus, more cases of serious and major incidents should be analysed and used for model learning.
- Regarding the computational limitation, minor incidents could be considered to complete the correlation between causes and failures. It might be interesting to check the behaviour of already established contribution paths with this new severity level in consideration.

Chapter 9.

9. CONCLUSION

In the next paragraphs, to conclude this dissertation, main research processes, analyses and results are gathered and discussed, as well as possible topics that derived from this concluded step and research works that would be developing forward are proposed.

9.1. Final Discussion

An air traffic accident is an undesirable occurrence that rarely occurred, but with fatal consequence. A lower number of accidents makes the scarce historical collected data conditional on the prediction of such catastrophic occurrences. In this thesis, we have proposed a global methodology, which contains three processes with the case study in two phases of development, essentially applying one expert-built incident model gathering the assessment of potential scenarios created by precursors to estimate accident.

In the first process, we have developed one novel method that allows the extraction of incident data from reports, reactivating the use of fishbone or Ishikawa diagrams as a sequential method in combination with the SOAM developed by EUROCONTROL, and with the ADREP taxonomy defined by ICAO. This proposal provides, from one side, a new interaction between traditional and new safety methods to pre-process information in safety occurrences; from other side, the advantage for possible computational application in incident investigation, i.e. Bayesian Network approach. During the development of this method, we have studied all incidents of severity A occurred during four consecutive years and other incidents of severity B limited only to commercial aviation during the same period. As the result of this process, one database of LOS incidents has been created for next processes of analysis.

In the second process, based on the data collected in the previous process, we have developed two BN models for LOS incident analysis as follows:

- i. One BN model has been created using all data of severity A incidents occurred during four consecutive years, including military and general aviation. This model has been used for explication and validation as purposes;
- ii. Other BN model has been created only focusing on commercial aviation, but the data cover all analysed LOS incidents of severity A and B. This BN model has a different purpose in deepening analyses and researching other possible developments.

BN model application to this particular incident category of LOS also demonstrated the acquisition of predictive quality, which would facilitate future official investigation in new incident scenarios, and the identity of precursors to MAC accident. As a reflection of this in-depth diagnostic to LOS, the concept of barrier adopts a new interpretation, which one barrier is not only imposed to reduce the likelihood of events, but also can be evaluated its efficiency on performance.

In the third process, we have applied Information Theory to the second BN model in detecting the precursors of LOS incidents as candidates to occur new incidents, as well as infer potential scenarios to MAC accidents as the prediction. Information Theory plays an essential role of assisting BN model in mutual information quantification, consequently, the identification of the most influential precursors and the establishment of rough predictive scenarios to anticipate the occurrence of major LOS or MAC.

Deviating from these results, the analysis have been deepened and led to develop the following points:

- Using likelihood estimated from BN model in a binary classifier, we have demonstrated that the non-incident operations performed are not easy to determine the details, but they are not necessary to be detected either. Then, with the data of incident operations, a new risk assessment matrix can be renovated based on the classic risk matrix combining the frequency of factors occurred only in incidents. Therefore, we can detect the most influential factors to accidents just focusing on rare cases.
- Applying Information Theory for two joints of incidents, we have detected the correlations between factors and incident levels are in accordance with what is described in Heinrich's Pyramid Theory. Then, the applicability of this theory for incidents occurred in ATM system is verified. Through Heinrich's Pyramid Theory, the concatenated factors that chain different safety levels can be identified and their impact on causing incidents of high severity level can be analysed and, assessed not only quantitatively, but also qualitatively. This conclusion allows us in reconsidering the

barrier design that should be able to mitigate the causes and not only the events as mechanisms in manifesting the causes.

However, certain limitations of application are presented with main causes such as following:

- Limitation in the data source: Due to the quantitative limitation presented on investigated incident data, part of BN model construction had to resort to expert knowledge. All incident data extracted from reports could be occurring in other ATM occurrence with less severity or none severity, so that the consequences of this missing data could affect the accuracy of the Information Theory approach.
- Limitation in the BN model: BN model is one of the most popular predictive models. However, the existence of uncertainties is inevitable in this kind of models. The correction or improvement of this deficiency requires that the update with new incident cases should be constantly to reduce the degree of uncertainty, and then the location of contrastive events or factors to the incident should be more accurate.

9.2. Roadmap for Future Work

In line with the arguments of the previous sections, this research project opens a door indicating multiple directions as topics for future works.

The transformation from SOAM analysis to ADREP taxonomy codification with the database creation leaves exploitation with safety models other than BN outstanding, models like FRAM or STAMP could be suitable candidates. This methodology also considers thoroughly the application to a dynamic BN model, which might provide different assessment for safety barrier efficiency.

The proposed BN model attempts to improve the current ATM system surveillance in real operations. Therefore, a new reduced ATM safety monitoring program might be developed and implemented in real operations. At the same time, with this program, BN model might be fed by real operational data for its improvement on the limitation in source data. Moreover, based on the result of Heinrich's Pyramid Theory application, another possible Bayesian-driven neuronal network model is proposed. This sophisticated prediction model could lead a new research topic related to artificial intelligent analysis with hidden layout controlled.

Finally, under SESAR environment in the short term, the integration of novel technologies into the present ATM systems should be evaluated quantitatively in risk reduction. Indeed, we consider that the proposed methodology and model are appropriate for such purpose.

INTENTIONALLY LEFT BLANK

LIST OF PUBLICATIONS

This PhD Thesis has led to the following published research papers:

Journal Papers

- R. M. Arnaldo Valdés, S. Z. Liang Cheng, V. F. Gómez Comendador, and F. J. Sáez Nieto, '*Application of Bayesian Networks and Information Theory to Estimate the Occurrence of Mid-Air Collisions Based on Accident Precursors*', Entropy, vol. 20, no. 12, p. 969, 2018.
- S. Z. Liang Cheng, R. M. Arnaldo Valdés, V. F. Gómez Comendador, and F. J. Sáez Nieto, '*A Case Study of Fishbone Sequential Diagram Application and ADREP Taxonomy Codification in Conventional ATM Incident Investigation*', Symmetry, MDPI, vol. 11, no. 4, 2019.
- S. Z. Liang Cheng, R. M. Arnaldo Valdés, V. F. Gómez Comendador, and F. J. Sáez Nieto, '*Detection of Common Causes between Air Traffic Serious and Major Incidents in Applying the Convolution Operator to Heinrich Pyramid Theory*', Entropy, MDPI, vol. 21, no. 12, 2019

Conference Proceeding

- S. Z. Liang Cheng, R. M. Arnaldo Valdés, V. F. Gómez Comendador, and R. Roman Cordon, '*Analysis of accident precursor data for Mid Air Collision occurrences using expert build Bayesian Network model and Information Theory*', in 8th European Conference for Aeronautics and Space Sciences (EUCASS), 2019.

INTENTIONALLY LEFT BLANK

BIBLIOGRAPHY

- [1] “London-Paris machines collide,” *Flight International*, 13-Apr-1922.
- [2] Bureau of Aircraft Accidents Archives, “Accident Archives.” [Online]. Available: <http://www.baaa-acro.com/crash-archives>.
- [3] Flight Safety Foundation, “ASN Aviation Safety Database.” [Online]. Available: <https://aviation-safety.net/database/>.
- [4] ICAO, “Annual Report 2018.”
- [5] IATA, “Press Release No. 62: IATA Forecast Predicts 8.2 billion Air Travelers in 2037,” 2018.
- [6] EASA, “EASA Annual Safety Review 2019,” 2019.
- [7] EUROCONTROL, “Performance Review Report (PRR) 2018,” 2018.
- [8] ICAO Annex 13, *International Standards and Recommended Practices Annex 13 to the Convention on International Civil Aviation Aircraft Accident and Incident Investigation*. ICAO, 2016.
- [9] V. M. Bier and W. Yi, “The performance of precursor-based estimators for rare event frequencies,” *Reliab. Eng. Syst. Saf.*, vol. 50, no. 3, pp. 241–251, 1995.
- [10] J. W. Johnson and D. M. Rasmuson, “The US NRC’s accident sequence precursor program: an overview and development of a Bayesian approach to estimate core damage frequency using precursor information,” *Reliab. Eng. Syst. Saf.*, vol. 53, no. 2, pp. 205–216, 1996.
- [11] C. Kirchsteiger, “Impact of accident precursors on risk estimates from accident databases,” *J. Loss Prev. Process Ind.*, vol. 10, no. 3, pp. 159–167, 1997.
- [12] J. R. Phimister, U. Oktem, P. R. Kleindorfer, and H. Kunreuther, “Near-Miss Incident Management in the Chemical Process Industry,” *Risk Anal.*, vol. 23, no. 3, pp. 445–459.

- [13] R. L. Dillon and C. H. Tinsley, "How Near-Misses Influence Decision Making Under Risk: A Missed Opportunity for Learning," *Manage. Sci.*, vol. 54, no. 8, pp. 1425–1440, 2008.
- [14] P. Eckle and P. Burgherr, "Bayesian Data Analysis of Severe Fatal Accident Risk in the Oil Chain," *Risk Anal.*, vol. 33, no. 1, pp. 146–160, 2013.
- [15] C. L. Smith and E. Borgonovo, "Decision Making During Nuclear Power Plant Incidents—A New Approach to the Evaluation of Precursor Events," *Risk Anal.*, vol. 27, no. 4, pp. 1027–1042, 2007.
- [16] N. Taleb, *The Black Swan: The Impact of the Highly Improbable*. New York: Pengu Random House, 2007.
- [17] N. Khakzad, F. Khan, and N. Paltrinieri, "On the application of near accident data to risk analysis of major accidents," *Reliab. Eng. Syst. Saf.*, vol. 126, pp. 116–125, 2014.
- [18] J. Quigley, T. Bedford, and L. Walls, "Estimating rate of occurrence of rare events with empirical bayes: A railway application," *Reliab. Eng. Syst. Saf.*, vol. 92, no. 5, pp. 619–627, 2007.
- [19] E. Perrin, B. Kirwan, and R. Stroup, "A Systematic Model of ATM Safety: the Integrated Risk Picture," 2006.
- [20] EUROCONTROL, "EAM 2/GUI 1 - Severity Classification Scheme for Safety Occurrences in ATM," 1999.
- [21] "2014 Safety Forum - Airborne Conflict." [Online]. Available: <https://www.flightdataservices.com/2014/05/29/%0Asafety-forum-airborne-conflict>.
- [22] EASA, "EOFDM Working Group A. Review of Mid Air Collision (MAC) Precursors from an FDM Perspective."
- [23] R. M. Arnaldo Valdés, V. F. Gómez Comendador, L. Perez Sanz, and A. Rodriguez Sanz, "Prediction of aircraft safety incidents using Bayesian inference and hierarchical structures," *Saf. Sci.*, vol. 104, pp. 216–230, 2018.
- [24] European Union, "Regulation (EU) No 376/2014 of the European Parliament and of the Council of 3 April 2014," 2014.

- [25] JOINT RESEARCH CENTRE, "ECCAIRS - European Co-ordination Centre for Accident and Incident Reporting Systems," *European Commission*. [Online]. Available: <https://eccairsportal.jrc.ec.europa.eu>.
- [26] L. Yu, Y. Yang, P. He, and H. Zhao, "A prototype system for aviation safety information exchanges based on international comparative research," 2010.
- [27] K. L. McFadden and E. R. Towell, "Aviation human factors: a framework for the new millennium," *J. Air Transp. Manag.*, vol. 5, pp. 177–184, 1999.
- [28] H.-J. Shyur, H. Keng, I.-K. I, and C.-L. Huang, "Using extended hazard regression model to assess the probability of aviation event," *Appl. Math. Comput.*, vol. 218, pp. 10647–10655, 2012.
- [29] J. Reason, "Managing the risks of organisational accidents," *Aldershot, UK Ashgate*, 1997.
- [30] J. Rasmussen, "Risk management in a dynamic society: a modelling problem," *Saf. Sci.*, vol. 27, pp. 183–213, 1997.
- [31] C. W. Johnson, B. Kirwan, A. Licu, and P. Stastny, "Recognition primed decision making and the organisational response to accidents: Überlingen and the challenges of safety improvement in European air traffic management," *Saf. Sci.*, vol. 47, pp. 853–872, 2009.
- [32] T. Licu, F. Cioran, B. Hayward, and A. Lowe, "EUROCONTROL—Systemic Occurrence Analysis Methodology (SOAM) - A 'Reason'-based organisational methodology for analysing incidents and accidents," *Reliab. Eng. Syst. Saf.*, vol. 92, pp. 1162–1169, 2007.
- [33] E. Hollnagel, *Safety I and Safety-II. The past and the future of safety management*. 2016.
- [34] A. R.Hale and J. Hovden, "Management and culture: The third age of safety. A review of approaches to organizational aspects of safety, health and environment," in *Occupational Injury: Risk, Prevention and Intervention*, A. M. Feyer and A. Williamson, Eds. Taylor & Francis Ltd, 2003, pp. 129–165.

- [35] A. I. Glendon, S. G. Clarke, and E. F. Mckenna, *Human safety and risk management*, 2nd ed. Taylor & Francis Ltd, 2006.
- [36] D. Borys, D. Else, and S. Leggett, "The fifth age of safety: the adaptive age?," *J. Heal. Saf. Res. Pract.*, vol. 1, no. 1, pp. 19–27.
- [37] N. Leveson, "A New Accident Model for Engineering Safer Systems," *Saf. Sci.*, vol. 42, no. 4, pp. 237–270.
- [38] J. Reason, *Human Error*, 20th ed. Cambridge University Press, 1990.
- [39] ICAO, *Safety Management Manual, (Doc 9859-AN/474)*. .
- [40] R. Patriarca, J. Bergström, G. Di Gravio, and F. Constantino, "Resilience engineering: Current status of the research and future challenges," *Saf. Sci.*, vol. 102, no. 79–100, 2018.
- [41] P. Underwood and P. Waterson, *Accident Analysis Models and Methods: Guidance for Safety Professionals*. Loughborough University, 2013.
- [42] J. Reason, "The Contribution of Latent Human Failures to the Breakdown of Complex Systems," *Philos. Trans. R. Soc. Lond. B. Biol. Sci.*, vol. 327, no. 1241, pp. 475–484, 1990.
- [43] EUROCONTROL, "Revisiting the Swiss cheese model of accidents," 2006.
- [44] EUROCONTROL & FAA, *U.S./Europe comparison of ATM-related Operational Performance*. Bruxells, 2012.
- [45] N. Leveson, *Engineering a Safer World: Systems Thinking Applied to Safety*. MIT press.
- [46] E. Hollnagel, *FRAM: The Functional Resonance Analysis Method : Modelling Complex Socio-technical Systems*. Taylor & Francis Ltd, 2012.
- [47] EUROCONTROL, *A white paper on resilience engineering for ATM*. Eurocontrol, 2009.
- [48] P. Underwood and P. Waterson, "Systems thinking, the Swiss Cheese Model and accident analysis: A comparative systemic analysis of the Grayrigg train derailment using the ATSB, AcciMap and STAMP models," *Accid. Anal. Prev.*, vol. 68,

- pp. 75–94, 2014.
- [49] D. Smith, B. Veitch, F. Khan, and R. Taylor, “Understanding industrial safety: Comparing Fault tree, Bayesian network, and FRAM approaches,” *J. LOSS Prev. Process Ind.*, vol. 45, pp. 88–101, 2017.
 - [50] R. Arnold, “A qualitative comparative analysis of SOAM and STAMP in ATM occurrence investigation,” Lund University, 2009.
 - [51] E. Hollnagel, “The changing nature of risks,” *Ergon. Aust. J.*, vol. 22, no. 1–2, pp. 33–46, 2008.
 - [52] C. Perrow, *Normal Accidents: Living with High Risk Technologies*, Updated ed. 1984.
 - [53] E. Hollnagel, “Anticipating Failures: What Should Predictions Be About?,” *Def. Tech. Inf. Cent. Compil. Part Not.*, 2001.
 - [54] E. Hollnagel, *Barriers and accident prevention*. Ashgate, 2004.
 - [55] P. Hudson, “Accident causation models, management and the law,” *J. Risk Res.*, vol. 17, no. 6, pp. 749–764, 2014.
 - [56] M. Yang, F. Khan, and L. Lye, “Precursor-based hierarchical Bayesian approach for rare event frequency estimation: A case of oil spill accidents,” *Process Saf. Environ. Prot.*, vol. 91, no. 5, pp. 333–342, 2013.
 - [57] M. Grazia Gnoni and J. H. Saleh, “Near-miss management systems and observability-in-depth: Handling safety incidents and accident precursors in light of safety principles,” *Saf. Sci.*, vol. 91, pp. 154–167, 2017.
 - [58] D. J. Spiegelhalter, A. P. Dawid, S. L. Lauritzen, and R. G. Cowell, “Bayesian analysis in expert systems,” *Stat. Sci.*, vol. 8, no. 3, pp. 219–247, 1993.
 - [59] EUROCONTROL, “ESARR 2 - REPORTING AND ASSESSMENT OF SAFETY OCCURRENCES IN ATM,” 2009.
 - [60] EUROCONTROL, “EAM 2/GUI 8 - GUIDELINES ON THE SYSTEMIC OCCURRENCE ANALYSIS METHODOLOGY (SOAM),” 2005.
 - [61] ICAO Annex 11, *International Standards and Recommended Practices Annex 11 to the Convention on International Civil Aviation Air Traffic Services*. 2016.

- [62] J. Chang and C. Lin, "A study of storage tank accidents," *J. LOSS Prev. Process Ind.*, vol. 19, no. 1, pp. 51–59, 2006.
- [63] K. Kunadharaju, T. D. Smith, and D. M. DeJoy, "Line-of-duty deaths among US firefighters: An analysis of fatality investigations," *Accid. Anal. Prev.*, vol. 43, no. 3, pp. 1171–1180, 2011.
- [64] O. Ferrante, P. Jouniaux, T. Loo, G. Nicolas, P. Cabon, and R. Mollard, "Application of ADREP 2000 taxonomy for the analysis and the encoding of aviation accidents and incidents: a human factors approach," *Hum. Factor Aerosp. Safety, Ashgate*, pp. 19–48, 2004.
- [65] ADREP taxonomy, "ICAO ADREP 2000 taxonomy," 2010.
- [66] Transportation Safety Board of Canada, "LOSS OF SEPARATION NAV CANADA Edmonton Area Control Centre Edmonton, Alberta 60 nm S 27 June 2002," 2002.
- [67] A. L. C. Roelen, P. H. Lin, and A. R. Hale, "Accident models and organisational factors in air transport: The need for multi-method models," *Saf. Sci.*, pp. 5–10, 2010.
- [68] B. J. M. Ale *et al.*, "Towards a causal model for air transport safety - an ongoing research project," *Sci. Direct*, vol. 44, pp. 657–673, 2006.
- [69] J. Skorupski, "The risk of an air accident as a result of a serious incident of the hybrid type," *Reliab. Eng. Syst. Saf.*, vol. 140, pp. 37–52, 2015.
- [70] C. Tang, Y. Yi, Z. Yang, and J. Sun, "Risk analysis of emergent water pollution accidents based on a Bayesian Network," *J. Environ. Manage.*, vol. 165, no. 199–205, 2016.
- [71] A.-A. Baksh, F. Khan, V. Gadag, and R. Ferdous, "Network based approach for predictive accident modelling," *Saf. Sci.*, vol. 80, pp. 247–287, 2015.
- [72] S. M. Deyab, M. Taleb-berrouane, F. Khan, and M. Yang, "Failure analysis of the offshore process component considering causation dependence," *Process Saf. Environ. Prot.*, vol. 113, pp. 220–232, 2018.
- [73] A. H. Ali, "Utilizing BADA (Base of Aircraft Data) as an On-Board Navigation Decision Support System in Commercial Aircrafts," *IEEE Intell. Transp. Syst. Mag.*, vol. 20,

- 2011.
- [74] M. C. G. S. P. Bandeira, A. Ribeiro Correia, and M. Ramos Martins, "Method for measuring factors that affect the performance of pilots," *Transportes*, vol. 25, pp. 156–169, 2017.
- [75] D. L. C. Mack, G. Biswas, X. D. Koutsoukos, and D. Mylaraswamy, "Learning Bayesian Network Structures to Augment Aircraft Diagnostic Reference Models," *IEEE Trans. Autom. Sci. Eng.*, vol. 14, pp. 358–369, 2017.
- [76] A. G. Wilson and A. V. Huzurbazar, "Bayesian networks for multilevel system reliability," *Reliab. Eng. Syst. Saf.*, pp. 1413–1420, 2006.
- [77] N. Khakzad, F. Khan, and P. Amyotte, "Safety analysis in process facilities: Comparison of fault tree and Bayesian network approaches," *Reliab. Eng. Syst. Saf.*, pp. 925–932, 2011.
- [78] J. Pearl, *Causality: Models, Reasoning and Inference*. Cambridge University Press, 2009.
- [79] S. Nadkarni and P. P. Shenoy, "A causal mapping approach to constructing Bayesian networks," *Decis. Support Syst.*, vol. 38, pp. 259–281, 2004.
- [80] E. Mendes, "Introducing the Expert-Base Knowledge Engineering of Bayesian Networks Process," in *Practitioner's Knowledge Representation*, Springer, 2014.
- [81] R. Squillante *et al.*, "Modeling accident scenarios from databases with missing data: A probabilistic approach for safety-related systems design," *Saf. Sci.*, vol. 104, pp. 119–134, 2018.
- [82] K. Przytula and D. Thompson, "Construction of Bayesian networks for diagnostics," in *IEEE AEROSPACE CONFERENCE PROCEEDINGS*, 2000.
- [83] M. H. Faber, D. Straub, E. Heredia-Zavoni, and R. Montes-Iturrizaga, "Risk assessment for structural design criteria of FPSO systems. Part I: Generic models and acceptance criteria," *Mar. Struct.*, vol. 28, pp. 120–133, 2012.
- [84] S. L. Lauritzen and D. J. Spiegelhalter, "Local Computations with Probabilities on Graphical Structures and Their Application to Expert Systems," *J. R. Stat. Soc. Ser. B*,

- vol. 50, no. 2, pp. 157–224, 1988.
- [85] F. V. Jensen, S. L. Lauritzen, and K. G. Olesen, “Bayesian updating in causal probabilistic networks by local computations,” *Comput. Stat. Q.*, vol. 4, pp. 269–282, 1990.
- [86] L. BayesFusion, “GeNIe Modeler,” 2018. [Online]. Available: https://support.bayesfusion.com/docs/GeNIe/index.html?learning_generatedatafile.html.
- [87] ENAIRE, “Annual Reports.” [Online]. Available: https://www.enaire.es/about_enaire/know_enaire/annual_reports/report.
- [88] CEANITA, “Informes definitivos.” [Online]. Available: https://www.seguridadaerea.gob.es/lang_castellano/g_r_seguridad/ceanita/informes_definitivos/default.aspx.
- [89] P. Brooker, “AIR TRAFFIC SAFETY: CONTINUED EVOLUTION OR A NEW PARADIGM,” *Aeronaut. J.*, vol. 112, pp. 333–344, 2008.
- [90] S. Hosseini, A. Al Khaled, and M. Sarder, “A general framework for assessing system resilience using Bayesian networks: A case study of sulfuric acid manufacturer,” *J. Manuf. Syst.*, vol. 41, pp. 211–227, 2016.
- [91] S. Hosseini and K. Barker, “Modeling infrastructure resilience using Bayesian networks: A case study of inland waterway ports,” *Comput. Ind. Eng.*, vol. 93, pp. 252–266, 2016.
- [92] S. Hosseini and K. Barker, “A Bayesian network model for resilience-based supplier selection,” *Int. J. Prod. Econ.*, vol. 180, pp. 68–87, 2016.
- [93] S. Hosseini and M. Sarder, “Development of a Bayesian network model for optimal site selection of electric vehicle charging station,” *Int. J. Electr. Power Energy Syst.*, vol. 105, pp. 110–122, 2019.
- [94] T. Aven, “On the Meaning of a Black Swan in a Risk Context,” *Saf. Sci.*, vol. 57, pp. 44–51, 2013.
- [95] J. F. Murphy and J. Conner, “Beware of the Black Swan: The Limitations of Risk

- Analysis for Predicting the Extreme Impact of Rare Process Safety Incidents,”
Process Saf. Prog., vol. 31, no. 4, pp. 330–333, 2012.
- [96] J. F. Murphy and J. Conner, “Black Swans, White Swans, and 50 Shades of Grey: Remembering the Lessons Learned from Catastrophic Process Safety Incidents,”
Process Saf. Prog., vol. 33, no. 2, pp. 110–114, 2013.
- [97] E. Paté-Cornell, “On ‘black swans’ and ‘perfect storms’: risk analysis and management when statistics are not enough,” *Risk Anal.*, vol. 32, no. 11, pp. 1823–1833, 2012.
- [98] S. Maslen and J. Hayes, “Preventing black swans: incident reporting systems as collective knowledge management,” *J. Risk Res.*, vol. 19, no. 10, pp. 1246–1260, 2016.
- [99] A. Kucuk Yilmaz, “Strategic approach to managing human factors risk in aircraft maintenance organization: risk mapping,” *Aircr. Eng. Aerosp. Technol.*, vol. 91, no. 1, 2019.
- [100] FAA, “AC 25-19A - Certification Maintenance Requirements,” 2011.
- [101] EASA, *Certification Specifications and Acceptable Means of Compliance for Large Aeroplanes CS-25 Amendment 23*. .
- [102] EUROCONTROL, “SRC DOC 1 - SAFETY MINIMA STUDY: Review of Existing Standards and Practices.”
- [103] EUROCONTROL, *EAM 4/GUI 4 - A METHOD FOR STATES TO DETERMINE NATIONAL ATM SAFETY MINIMA*. .
- [104] E. J. García González, “DEVELOPMENT OF A 3-DIMENSIONAL MATHEMATICAL COLLISION RISK MODEL BASED ON RECORDED AIRCRAFT TRAJECTORIES TO ESTIMATE THE SAFETY LEVEL IN HIGH DENSITY EN-ROUTE AIRSPACES,” 2013.
- [105] EUROCONTROL, “ESARR 4 - RISK ASSESSMENT AND MITIGATION IN ATM.”
- [106] EUROCONTROL, *RAT Guidance Material*, V2.0. 2015.
- [107] EUROCONTROL, “European Network Operations Plan 2019-2024.”

- [108] H. W. Heinrich, *Industrial Accident Prevention: a Scientific Approach*. McGraw-Hill, 1931.
- [109] G. Walker, "Redefining the incidents to learn from: Safety science insights acquired on the journey from black boxes to Flight Data Monitoring," *Saf. Sci.*, vol. 99, no. Part A, pp. 14–22, 2017.
- [110] H. W. Heinrich, N. R. Roos, and D. C. Petersen, *Industrial accident prevention: A safety management approach*. McGraw-Hill, 1980.
- [111] A. Johnson, "Examining the foundation," in *National Safety Council Congress & Expo*, 2018.
- [112] S. Sultana, B. S. Andersen, and S. Haugen, "Identifying safety indicators for safety performance measurement using a system engineering approach," *Process Saf. Environ. Prot.*, vol. 128, pp. 107–120, 2019.
- [113] M. Kyriakidis, R. Hirsch, and A. Majumdar, "Metro railway safety: An analysis of accident precursors," *Saf. Sci.*, vol. 50, no. 7, pp. 1535–1548, 2012.
- [114] O. Golovina, M. Perschewski, J. Teizer, and M. König, "Algorithm for quantitative analysis of close call events and personalized feedback in construction safety," *Autom. Constr.*, vol. 99, pp. 206–222, 2019.
- [115] P. Marshall, A. Hirmas, and M. Singer, "Heinrich's pyramid and occupational safety: A statistical validation methodology," *Saf. Sci.*, vol. 101, pp. 180–189, 2018.
- [116] K. P. Prem, D. Ng, and M. S. Mannan, "Harnessing database resources for understanding the profile of chemical process industry incidents," *J. Loss Prev. Process Ind.*, vol. 23, no. 4, pp. 549–560, 2010.
- [117] A. Majumdar, M.-D. Dupuy, W. Y. Ochieng, and P. Nalder, "Developing Safety Indicators for New Zealand Airspace: Analysis of Loss-of-Separation Incidents," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 1951, no. 1, pp. 86–97, 2006.
- [118] Z. Nazeri, G. Donohue, and L. Sherry, "Analyzing Relationships Between Aircraft Accidents and Incidents," in *International Conference on Research in Air Transportation (ICRAT 2008)*, 2008.

- [119] N. K. Kim, K. M. Jeon, and H. K. Kim, "Convolutional Recurrent Neural Network-Based Event Detection in Tunnels Using Multiple Microphones," *sensors*, vol. 19, no. 12, 2019.
- [120] K. Nan, S. Liu, J. Du, and H. Liu, "Deep model compression for mobile platforms: A survey," *Tsinghua Sci. Technol.*, vol. 24, no. 6, pp. 677–693, 2019.
- [121] S. Z. Liang Cheng, R. M. Arnaldo Valdés, V. F. Gómez Comendador, and F. J. Sáez Nieto, "A Case Study of Fishbone Sequential Diagram Application and ADREP Taxonomy Codification in Conventional ATM Incident Investigation," *Symmetry, MDPI*, vol. 11, no. 4, 2019.
- [122] S. B. Damelin and W. Miller, *The mathematics of signal processing*. Cambridge University Press, 2011.
- [123] X. Hu, H. Zhang, D. Ma, and R. Wang, "Status detection from spatial-temporal data in pipeline network using data transformation convolutional neural network," *Neurocomputing*, vol. 358, pp. 401–413, 2019.
- [124] H. D. Nguyen and G. McLachlan, "On approximations via convolution-defined mixture models," *Commun. Stat. - Theory Methods*, vol. 48, no. 16, pp. 3945–3955, 2019.
- [125] W. Huang, K. K. Lai, J. Zhang, and Y. Bao, "Foreign Exchange Rates Forecasting with Multilayer Perceptrons Neural Network by Bayesian Learning," in *2008 Fourth International Conference on Natural Computation*, 2008.
- [126] B. Abdulhai and S. G. Ritchie, "Enhancing the universality and transferability of freeway incident detection using a Bayesian-based neural network," *Transp. Res. Part C Emerg. Technol.*, vol. 7, no. 5, pp. 261–280, 1999.
- [127] P. Gupta and J. Schumann, "A tool for verification and validation of neural network based adaptive controllers for high assurance systems," in *Eighth IEEE International Symposium on High Assurance Systems Engineering*, 2004.

INTENTIONALLY LEFT BLANK

APPENDIX A

APPENDIX A – ATM INCIDENT DATABASE NORMALIZATION

In this appendix, the processes related to our database normalization are detailed, as well as the design with Microsoft Access is presented.

A.1 INTRODUCTION

A database is a collection of data that is used providing support to different activities of a particular organization. A database can be considered as a dynamic repository of data that would be extended with new data but with defined structure of organization. Each data contains specific information that is considered as attribute and recorded in entities (tables). The normalization of a database is a formal process for assigning attributes to entities, and should be part of the database design process.

Normalization procedure usually focuses on characteristics of specific entities making the goals, such that the database design may be more efficient, the amount of redundant data stored may be reduced, and anomalies may be avoided when updating, inserting or deleting data. Normalization Process Theory (NPT) provides a tool to delineate normalization in different ways. Generally, four normal forms (NF) are defined and used with more frequently:

- First normal form (1NF)
- Second normal form (2NF)
- Third normal form (3NF)
- Boyce-Codd normal form (BCNF)

Each normal form involves a set of dependency properties with a proper schema to be satisfied. In this way, each normal form ensures the presence / absence of update anomalies.

A.2 DEPENDENCY DIAGRAM

In our case, we have an original table (Figure Appendix A-1) that contains all information related to the analysis of ATM serious and major incident reports. Firstly, we should clean this table making that every row does not contain null information (Figure Appendix A-2).

1	Report_ID	Severity	Event_ID	Event_Lvl	Event_Num	Event_Def	DF_ID	DF_Lvl	DF_Num	DF_Def
2	022_14	A	4070400	3	1	Air space capacity reduction: An event involving the effect of an air space capacity reduction on Air Traffic Management operations.	24010107	5	2	Air traffic control requirement for the acknowledgement of information by the flight crew
3							12251500	4	3	Flight crew's action in respect to air traffic control clearance: Air traffic control clearance. Authorization for an aircraft to proceed under conditions specified by an air traffic control unit.
4			4010200	3	2	Air Navigation Services operational information provisions: An event involving Air Navigation Services operational information provisions.	24010703	5	4	Air traffic control provision of flight information
5			2020300	3	4	Communication between pilot and air navigation service related event: An event related to the communication between the pilot and the air navigation service. This is not to be used when there was a technical difficulty related to the communication.	12252600	4	6	Flight crew's air/ground/air communication: Air-ground communication. Two-way communication between aircraft and stations or locations on the surface of the earth.
6							24010102	5	7	Air traffic control use of readback/hearback error detection: Readback. A procedure whereby the receiving station repeats a received message or an appropriate part thereof back to the transmitting station so as to obtain confirmation of correct reception. ICAO Annex
7			2020202	4	5	Air navigation service clearance to wrong altitude: An event related to a clearance to the wrong altitude by the ANS services.	22120100	4	9	Air traffic management's strategic planning for conflict detection
8	066_14	A	5010103	4	1	Precision approach radar related event: An event involving a precision approach radar.	21020106	5	1	Air traffic management's use of the precision approach radar: Precision approach radar: A high-definition, short-range radar used as an approach aid. This system provides the controller with altitude, azimuth and range information of high accuracy for the purpose of assisting the pilot in executing an approach and landing. This form of navigation assistance is termed a 'precision radar approach.'
9							21030102	5	2	Air traffic management's use of radar data processing system
			2020300	3	2	Communication between pilot and air navigation service related event: An event related to the communication between the	24010102	5	3	Air traffic control use of readback/hearback error detection: Readback. A procedure whereby the receiving

Figure Appendix A-1 – Original table of ATM incident reports

APPENDIX A – ATM INCIDENT DATABASE NORMALIZATION

	Report_ID	Severity	Event_ID	Event_Ivl	Event_Num	Event_Def	DF_ID	DF_Ivl	DF_Num	DF_Def
1	022_14	A	4070400	3	1	Air space capacity reduction: An event involving the effect of an air space capacity reduction on Air Traffic Management operations.	24010107	5	2	Air traffic control requirement for the acknowledgement of information by the flight crew
2	022_14	A	4070400	3	1	Air space capacity reduction: An event involving the effect of an air space capacity reduction on Air Traffic Management operations.	12251500	4	3	Flight crew's action in respect to air traffic control clearance: Air traffic control clearance. Authorization for an aircraft to proceed under conditions specified by an air traffic control unit.
3	022_14	A	4010200	3	2	Air Navigation Services operational information provisions: An event involving Air Navigation Services operational information provisions.	24010703	5	4	Air traffic control provision of flight information
4	022_14	A	2020300	3	4	Communication between pilot and air navigation service related event: An event related to the communication between the pilot and the air navigation service. This is not to be used when there was a technical difficulty related to the communication.	12252600	4	6	Flight crew's air/ground/air communication: Air-ground communication. Two-way communication between aircraft and stations or locations on the surface of the earth.
5	022_14	A	2020300	3	4	Communication between pilot and air navigation service related event: An event related to the communication between the pilot and the air navigation service. This is not to be used when there was a technical difficulty related to the communication.	24010102	5	7	Air traffic control use of readback/hearback error detection: Readback: A procedure whereby the receiving station repeats a received message or an appropriate part thereof back to the transmitting station so as to obtain confirmation of correct reception. ICAO Annex
6	022_14	A	2020202	4	5	Air navigation service clearance to wrong altitude: An event related to a clearance to the wrong altitude by the ANS services.	22120100	4	9	Air traffic management's strategic planning for conflict detection
7	066_14	A	5010109	4	1	Precision approach radar related event: An event involving a precision approach radar.	21020106	5	1	Air traffic management's use of the precision approach radar: Precision approach radar: A high-definition, short-range radar used as an approach aid. This system provides the controller with altitude, azimuth and range information of high accuracy for the purpose of assisting the pilot in executing an approach and landing. This form of navigation assistance is termed a 'precision radar approach.'
8	066_14	A	5010109	4	1	Precision approach radar related event: An event involving a precision approach radar.	21030102	5	2	Air traffic management's use of radar data processing system
9	066_14	A	2020300	3	2	Communication between pilot and air navigation service related event:	24010102	5	3	Air traffic control use of readback/hearback error detection:

Figure Appendix A-2 – Cleaned table of ATM incident reports

Then we have a completed table named: ATM_Incident_Report (Report_ID, Severity, Event_ID, Event_Ivl, Event_Num, Event_Def, DF_ID, DF_Ivl, DF_Num, DF_Def), which contains repeating groups.

In order to normalize this database, it is necessary to understand the relationship of dependency. Figure Appendix A-3 represents the dependency diagram for this database normalization process. We have intentionally created the dependency between DF and Event due to the objective of the analysis. Then Report_ID and Event_ID are identified as the primary keys.

Figure Appendix A-3 – Dependency diagram

A.3 FIRST NORMAL FORM (1NF)

In the first normal form, there are no repeating groups, at the intersection of each row and column only single values are permitted, hence the relation is if and only if the domain of each attribute contains only indivisible values, and the value of each attribute contains only a single value from that domain.

To normalize a relation that contains a repeating group, remove the repeating group and form two new relations. Then, in first normal form process we have two tables created:

- Incident_ID (Report_PK, Report_ID, Severity). A table is now in first normal form with the repeating group removed. Although previously the attribute Report_ID is identified as primary key, however due to its property of data type as indicated in Figure Appendix A-4, Report_PK is created with property of number as ACCESS program allowed.

	Field Name	Data Type
	Report_PK	AutoNumber
	Report_ID	Short Text
	Severity	Short Text

Figure Appendix A-4 – Incident_ID table design view

- IncidentContent (Report_ID, Event_ID, Event_IVI, Event_Num, Event_Def, DF_ID, DF_IVI, DF_Num, DF_Def).

A.4 SECOND NORMAL FORM (2NF)

For the second normal form, the relation is automatically in 2NF if, and only if, the primary key comprises a single attribute. In this stage, if the relation has a composite primary key like the table IncidentContent, then it is divided in two other tables removing the full dependencies and only one primary key is defined in each table:

- Case (ID, Report_PK, Occurrence_PK)
- Occurrences (Occurrence_ID, Event_ID, Event_lvl, Event_Num, Event_Def, DF_ID, DF_lvl, DF_Num, DF_Def). Occurrence_ID is created as primary key for Occurrence table due to the same reason as for Incident_ID table.
- Incident_ID (Report_PK, Report_ID, Severity).

A.5 THIRD NORMAL FORM (3NF)

In the third normal form, all transitive dependencies should be removed. As the result, we have next tables:

- Case (ID, Report_PK, Occurrence_PK)
- Occurrences (Occurrence_ID, Event_ID, Event_Num, DF_ID, DF_Num)
- Incident_ID (Report_PK, Report_ID, Severity).
- Event_ADREP (Event_ID, Event_Ivl, Event_Def)
- DF_ADREP (DF_ID, DF_Ivl, DF_Def)

A.6 BOYCE-CODD NORMAL FORM (BCNF)

This situation is occurred when a table has more than one candidate key presented, then Boyce-Codd normal form is a special case of 3NF. A relation is in BCNF if, and only if, every determinant is a candidate key.

In our database, we have not any other alternative primary key candidates.

A.7 NORMALIZATION AND DATABASE DESIGN

Figure Appendix A-5 summarizes the relationship established for our database with Microsoft ACCESS program. With this relationship we can make different queries like the detection of repeated DF in the same report. Note that this relationship is only part of the full database that we have created, i.e., Event_ADREP and DF_ADREP tables are connected with ADREP taxonomy database, which has been created in another project.

Figure Appendix A-5 – Database relationship in ACCESS

INTENTIONALLY LEFT BLANK

APPENDIX B

APPENDIX B – ADREP TAXONOMY CODE

In this appendix, ADREP taxonomy codes used for the development of this thesis are presented in following tables.

B.1 TAXONOMY CODES OF EVENTS

Event Code	Event Description
1230000	Communication systems
2020201	ANS erroneous clearance
2020202	ANS clearance to wrong altitude
2020300	Communication between pilot and ANS
2020505	Clearance deviation - take-off
2020506	Clearance deviation - en-route
2020508	Clearance deviation - approach
2020509	Clearance deviation - holding
2020513	Clearance deviation - special procedure
2020517	Deviation from clearance - assigned flight level
2020519	Deviation from clearance - assigned or specified speed
2020522	Deviation from clearance - climb/descent conditional clearance
2020805	Deviation from approach procedure
2100100	Diversion due to weather conditions
2170200	Wrong runway selected
4010100	ANS operational communications
4010200	ANS operational information provisions
4010300	ANS separation provision
4010400	ANS conflict detection and resolution
4010500	ANS handling of accidents/incidents/emergency
4010600	ANS handing over/taking over procedure
4050300	Failure of surveillance
4070400	Air space capacity reduction

Table Appendix B-1 – Associated events in severity A and B when DF 24010102 in present state

B.2 TAXONOMY CODES OF DESCRIPTIVE FACTORS

Descriptive Factor Code	Descriptive Factor Description
11222000	Speed-attitude correction system
12210500	Pilot's perception of visual/oral warning
12210900	Pilot's obstacle clearance judgement
12230900	Pilot's operation of emergency brakes
12232800	Pilot's operation of communication equipment
12240600	The rate of descent of the aircraft
12240700	The flying speed of the aircraft
12251400	Pilot's action in respect to instruction
12251500	Pilot's action in respect to ATC clearance
12251800	Pilot's radiotelephony phraseology
12252200	Pilot's action in respect to standard operating procedure
12252600	Pilot's air/ground/air communication
21010900	Headsets
21020103	ATM's use of the instrument landing system
21030401	ATM's use of secondary area radar
21040200	ATM's information data system
22050100	A/C performance differences
22060100	ATM's monitoring of A/C
22060200	ATM's monitoring of frequencies
22080101	ATM's internal coordination of civil sectors in the same unit
22080103	ATM's internal coordination of military sectors in the same unit
22080201	ATM's coordination with an adjacent civil unit
22080203	ATM's coordination with an adjacent civil sector
22080303	Revision of ATM's coordination procedures
22090000	ATM's traffic transfer
22100300	Airspace during the hand-over/take-over
22100600	Briefing for the hand-over/take-over
22100700	Familiarization with traffic during the hand-over/take-over
22110200	ATM's updating of a flight plan
22120100	ATM's strategic planning for conflict detection
22120200	ATM's tactical execution of the conflict detection strategy
22130101	ATM's horizontal conflict resolution by radar vectoring/monitoring
22130200	ATM's vertical conflict resolution
22130300	ATM's conflict resolution by planned controller action
23010200	AWY/Route approach procedure
23010201	Surveillance radar element of a precision approach radar system approach
23010300	Clearance procedure
23010700	Emergency procedure
23020300	ATC use of approach procedure

Descriptive Factor Code	Descriptive Factor Description
23020400	ATC use of clearance procedure
23020500	ATC use of climb procedure
23020600	ATC use of departure procedure
23020700	ATC use of descent procedure
23020800	ATC use of emergency procedure
23021100	ATC use of holding procedure
24010101	ATC use of phraseology
24010102	ATC use of readback/hearback error detection
24010103	Blocked communication
24010105	ATC call-sign confusion
24010106	ATC transfer of communication
24010107	ATC requirement for the acknowledgement of information by the Pilot
24010301	ATC requirement for the acknowledgement of information by the ATCO
24010304	Information input error in the ATC operations
24010604	ATC provision of a short term conflict alert (STCA) warning
24010605	ATC provision of airborne proximity warning
24010703	ATC provision of flight information
24010704	ATC provision of a minimum safe flight level/altitude/height/sector altitude
24010705	ATC provision of delay related information
25050000	ATM service personnel operating procedures/instructions
26070000	ATM handling of A/C unusual/emergency situation
27010300	ATC rostering/sector opening in relation to expected traffic
27030000	ATC monitoring of sector traffic load
27050200	Factors relating coordination with ATFM
27060100	ATC assistance to the ATC in recovering control of traffic
41100300	Runway obstruction
52010200	Instrument meteorological conditions
52020400	Tailwind
52020500	Crosswind
52021200	Turbulence in cloud
52031400	Cloud amount restricting visibility
52031600	Thunderstorm

Table Appendix B-2 – Associated events in severity A and B when DF 24010102 in present state