Australasian Transport Research Forum 2019 Proceedings
30 September – 2 October, Canberra, Australia
Publication website: http://www.atrf.info

# Factors affecting unmanned aerial vehicles' safety: a post-occurrence exploratory data analysis of drones' accidents and incidents in Australia

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"This is an abridged version of the paper presented at the conference. The full version is being submitted elsewhere. Details on the full paper can be obtained from the author(s)."

# 1. Introduction

Unmanned aerial vehicles (UAV) have made life easier in many ways, and their applications in civil practice are increasing rapidly. However, this benefit is not entirely risk-free, as unwanted accidents and incidents can cause serious harm and interrupt other aerial activities. In this paper, we investigate a dataset of UAV accidents and incidents in Australia and put up some precautionary exercises to reduce the risk of future events. To that end, univariate and bivariate distributions of past events are analysed, and the exploratory factor analysis technique is used to identify frequent accident and incident patterns. The findings show that equipment issues or/and lack of coordination between aerial activities are two of the accidents and incidents categories; therefore, necessitating regular safety inspections for UAVs and establishing an integrated monitoring system for aerial activities are expected to reduce the risk of accidents and incidents.

In the last 10 years, rather than military purposes, a wide range of commercial applications for drones have been introduced, such as: remote sensing and 3D mapping (Nex and Remondino, 2014, Colomina and Molina, 2014), infrastructure maintenance (Ham et al., 2016, Máthé and Buşoniu, 2015), disaster management (D'Onfro, 2014, Deruyck et al., 2016, Quaritsch et al., 2010), real estate (Luppicini and So, 2016), safety (Irizarry et al., 2012), construction (Hubbard et al., 2015, Liu et al., 2014), mining (Lee and Choi, 2016), agriculture (Zhang and Kovacs, 2012, Tokekar et al., 2016) and cargo (Iwata and Matsumoto, 2013). One of the main reasons behind drones' numerous applications is the ability of mounting high-quality cameras or precise sensors on these flying machines, which provide a chance to reduce the cost of data gathering or accomplishing many desired tasks.

The rapidly growing market of drones had a value of 27 billion US dollars in 2016 and was expected to reach a total value of 100 billion dollars between 2017 and 2020 (Sachs, 2016). This growth will provide a considerable number of job opportunities in businesses especially in construction, agriculture, insurance, and oil/gas. According to the Goldman Sachs Research report, it is expected that in 2020 around 8 million shipments will be handled by small drones (Sachs, 2016). At the moment over 800 million US dollars is spent for drones in the firefighting industry specifically for scene monitoring, search and rescue, post-fire assessment and jungle firefighting (Gettinger, 2017). A study in 2017 manifested that in the US more than 340 agencies including police, sheriff, fire, state government, and city councils are actively using drones (Gettinger, 2017). This figure shows over 500% increase in the number of agencies using drones in only two years (Gettinger, 2017).

While useful and with versatile applications, overlooking safety regulations around UAVs might result in disastrous outcomes. Although currently, drones' life-threatening failures are rare, given the growing use of drones, if no preventive and precautionary action is taken, safety becomes a major issue in the near future. Currently, the operation of small drones is limited to visual sight of the ground controller that decreases the potential applications of the small UAVs (Clarke, 2014). There is a controversial dialogue around the legal enforcement for small UAVs to enforce some restriction on small drones' operations. This could provide a safer public environment; however, businesses analytics believe that these limits will lead to losing a considerable number of job opportunities in the market (Perritt Jr and Sprague, 2016).

Australian Transport Safety Bureau (ATSB) recently has published a report about the growing safety concerns about the UASs (Bureau, 2017). This report reviews the reported collisions of small UAVs within 2012-2016. According to this report, most of the collision records occurred in 2016, around 40% of the collisions are related to ground control while only 10% of accidents caused by technical issues including engine breakdown.

In this paper, we focus on the collision of commercial UAVs to extract prevailing patterns in the observed accidents and incidents which can help with developing effective legislation and regulation for UAV operations. We believe, on one hand, there is a big technological difference between military and commercial drones, and on the other hand, the functionality and purpose of small drones is drastically different from the manned aircraft. Therefore, neither the safety procedure for military drones, nor the existing regulations and procedures for manned aircraft cannot be simply adapted to off-the-shelf consumer drones. The distinctive performance and applications of commercial drones necessitate a tailor-made and comprehensive legislation around drone operations. The comprehensive legislation is meant to reduce the rate of accidents by providing appropriate safety procedures, and more importantly, should clarify responsibilities and liabilities in case of accidents. The latter one is essential for the business to grow, as without a clear vision about risks and rewards, insurance and financial firms are reluctant to participate in the market. Currently in Australia, the civil and aviation safety authority (CASA) strongly recommend organisations to consider third party personal and property insurance or UAV insurance as a part of their business, however, there is no regulatory requirement from CASA. Types of insurance are applicable to drone users: HULL and operation insurance. HULL insurance covers the damage or loss to the UAV, and operation insurance covers any damage to third party.

# 2. Data

The dataset of this study is obtained from the Australian Transport Safety Bureau (ATSB). The main aim of ATSB is improving safety and public confidence for all modes of transport, including aviation. The dataset includes 138 records of accidents and incidents for UAS under civil operation from June 2000 to June 2018 across Australia. It is noteworthy to mention that these accidents are only the ones that have been reported to ATSB. It is plausible to assume it is more likely for sever accidents to be reported, which means the less sever accidents are underrepresented in this study. The original dataset includes the date and location of the occurrence, the details of the UAV and a short summary about the occurrence. Based on the severity of the occurrence, the records are classified in three levels of *accident*, *serious incident* and *incident*, where accidents are the most severe collisions and incidents the least sever ones.

## 2.1. Occurrence category

- *Awareness*. Refers to all accidents and incidents that pilot's loss of awareness about the location of UAV has led to the occurrence.
- *Bird*. This category is adapted from CICTT and refers to bird strikes.
- *Collision*. This category includes collision to any obstacle and barrier except for birds. CICTT has a category called "collision with obstacle(s) during take-off and landing (CTOL)", but as the operation altitude for UAV is not as high

as the commercial aircrafts, we modified this category to include collisions during hovering and cruise as well.

- *Near occurrence*. Includes all the near collisions between two UAVs or between a UAV and other aerial vehicles and objects such as manned aircrafts and parachutes. It also includes cases when a UAV interrupts or is sighted in the proximity of another UAV, or manned aircraft (ATSB, 2017). This category is a modified version of “airprox/ TCAS alert/ loss of separation/near midair collisions/midair collisions (MAC)” in CCITT (CICTT, 2011).
- *Navigation*. Refers to all the cases, where the navigation of UAS is the cause of accident or incident. This category is a sub-category of “air traffic management or communications, navigation, or surveillance service issues” (ATM) by CICTT.
- *System component failure – non-power plant (SCF-NP*). The definition of this variable in CICTT includes a clause about unmanned aircraft: *“includes failure or malfunction of ground-based, transmission, or aircraft-based communication systems or components –or– datalink systems or components”*. We used the same definition here.
- *System component failure – power plant (SCF-PP).* This category is also adapted from CICTT and it includes failures or malfunctions related to the battery and power plant controls of the UAS.
- *Loss of ground control (LGC).* Includes all the cases where losing the control of UAV is the cause of accident or incident. Note that, CICTT has two categories called “loss of control – ground” and “loss of control – inflight” but the definition of these variables is different from LGC. Loss of ground control occurs due to three major reasons: equipment failure where either the UAV or the controller does not respond properly, increasing the distance between the UAV and the controller, and electro-magnetic interference which can affect the communications.

- *Turbulence*. Directly extracted from CICTT, refers to encounters with turbulence.

## 2.2. Hazard category

- *Environmental*. This label is used when the cause of occurrence is a factor of the environment, such as severe weather events. This label is also used for the cases where bird strike is the cause of occurrence.
- *Technical*. This category refers to the cases where technical deficiencies have caused the accident or incident.
- *Organisational*. This category is defined by CICTT to identify the cases where operational policies, procedures, and organisational regulations are the cause of occurrence. We used this label to the cases where lack of coordination between UAS operators and other organisations.
- *Human*. This category encompasses physical, medical, cognitive and psychological functioning of involved humans.

## 2.3. Phase of flight

- *Take-off*. From detaching from the ground, or pilot's hands, until reaching the operational altitude.
- *Landing*. from reducing altitude for landing purpose until UAV touches the ground. This phase includes non-conventional landing methods such as using parachute.
- *Cruise*. All the phases that cannot be labeled as *take-off* or *landing*. This includes cruising, hovering and changing altitude while completing the pre-assigned tasks.

## 2.4. Colliding object

- Terrain
- Water
- Tree
- Other solid objects
- Bird
- Human

## 2.5. Operation type

- Survey
- Training
- Test
- Agriculture
- Emergency medical service (EMS)
- Rescue

# 3. Methodology

This study uses the exploratory factor analysis (EFA) method to reduce the dimensionality of observed variables and represent them in a more tractable form with a fewer number of latent variables (Tryfos, 1998). EFA investigates whether the observed variables $\boldsymbol{x} = (x_1, \dots x_p)$ can be summarized by a set of unobserved factors (aka latent variables) $\boldsymbol{f} = (f_1, \dots, f_q)$. The underlying relationship between observed variables and latent variables is assumed to be a stochastic as formulated in equation (1) (Bartholomew, 1980). In this equation, $g(\boldsymbol{x})$ and $h(\boldsymbol{f})$ are the joint distribution functions of the observed and latent variables respectively, and $\pi(\boldsymbol{x}|\boldsymbol{f})$ is the conditional probability function of $\boldsymbol{x}$ given $\boldsymbol{f}$. The integral is defined over $\mathcal{R}$ which is the range space of the latent variables.

$$g(\boldsymbol{x}) = \int_{\mathcal{R}} \pi(\boldsymbol{x}|\boldsymbol{f})\, h(\boldsymbol{f}) d\boldsymbol{f} \tag{1}$$

Under several simplifying assumptions, for an available set of $n$ observation with $p$ attributes, equation (2) illustrates the relationship between observed values and latent factors. In this equation, $X_{n \times p}$ is the standardised matrix of observed variables.

In this matrix, the $n$ observations are stacked on top of each other. $\Phi_{q\times p}$ is the matrix of factor loadings, and $\boldsymbol{\varepsilon_{n\times p}}$ is the matrix of error terms, which represents the stochasticity.

$$X = F\Phi + \varepsilon \tag{2}$$

Several methods are available for estimating the parameters of the model. In this study, we use the maximum likelihood method, and for that purpose, we need to make an additional assumption on the distribution of the factors. The usual assumption is that $f_i \sim \mathcal{N}(0,1)$ and factors are independent with each other and across observations (Shalizi, 2013). The likelihood function for estimating the parameters of the model is as equation (3). In this equation $\hat{v}$ is the covariance matrix for the observed sample, and tr(.) is trace of a matrix.

$$\mathcal{L} = -\frac{np}{2} log2\pi - \frac{n}{2}\log|\psi - \phi^T\phi| - \frac{n}{2}\ tr((\psi - \phi^T\phi)^{-1}\ \hat{v} \tag{3}$$

## 4. Results

The analyses of this study are presented in two sections. First, the descriptive statistics of the data is discussed, and then the results of the exploratory factor analysis are presented.

### 4.1. Univariate distribution analysis

After categorising the occurrence records of this study, the frequencies of variables are visualised to assist with exploring existing patterns in the data. There are eight categorical variables, including “accident category”, and each category has multiple levels. As mentioned before, we use quotation marks when referring to “variables” and italic style when referring to their *levels*. The *unknown* cases are omitted from these distributions to avoid biasedness in the interpretation. The omitted cases are less than 10% of the records for all the variables except for “hazard category” and “colliding object”. Only in 86 records out of the 138 accidents and incidents the “hazard category” was identifiable, which means 38% of the records are removed for this variable. Moreover, in 17% of the records, the object to which the UAV had collided was not clear, thereby removed from the distribution for “colliding object”.

According to the distributions, in most cases, the UAV has directly collided into the *terrain*. Water is the next frequent item in a collision, but in this category, there is no case of incident or serious incident. This is because finding a UAV after it has sunk into water is somehow impossible and all the cases where the UAV is not retrieved are labelled as an accident.

For “Hazard category”, *equipment factor* is the most frequent category, and *human factors* is the least frequent one. After removing the 52 cases for which this variable was *unknown*, the hazard category for 61% of the accidents and incidents was equipment problems.

The breakdown of “occurrence category” shows that *loss of ground control (LGC)* with 31% is the most frequent category. It is followed by *non-power plant system component failure (SCF-NP)* with a percentage of 25%. After that comes *power plant* *system component failure (SCF-PP)* and *collision* with 10% and then the rest of occurrence categories are all below 10%.

Regarding the “operation type”, most of the accidents and incidents (nearly 77%) were during *survey* which includes video recording, laser scanning, and image taking. After *survey*, all other operation categories have a percentage below 10.

The distribution plot for “phase of flight” shows that nearly 80% of accidents and incidents occurred while aircrafts are hovering or cruising, whereas only 8% of them happened during *take-off*.

Finally, the breakdown of records for the “states and territories” shows that *Queensland* and *Western Australia* with 34% and 25% of accidents and incidents are the first two states with the highest number of occurrences, and *Australian Capital Territory* and *South Australia* with 2% and 4% are the regions with the lowest percentages.

## 4.2. Exploratory factor analysis

The EFA of this study is conducted with the assistance *psych* package in the statistical software package of *R*. To decide about the suitable number of factors, the value of eigenvalues for various number of factors is considered. As a rule of thumb (Revelle and Rocklin, 1979), cases where the eigenvalue of factors is less than 1 are not suitable. This rule leaves us with the maximum number of seven factors. In this study, we develop all the factor models with number of factors from 7 to 1 and select the most suitable model, which is parsimonious in number of factors yet enlightening in terms of summarising observed data into distinct occurrence categories.

The most suitable factor model turned out to include 5 factors. This number of factors is exactly what the rule of thumb (Revelle and Rocklin, 1979) suggested.

The EFA practice of this study summarises the observed accidents and incidents using five factors. Each factor can be a representative of a common type of collision.

- Factor 1: Loss of awareness

This factor represents cases where loss of awareness is the “cause of occurrence”. The “hazard category” for this factor is primarily noted as *human factors*, and this type of collision is more frequent during the landing phase.

- Factor 2: Bird strike

As the name implies, this category includes all collisions where bird strike occurs. The “hazard category” for accidents and incidents that contributes to this factor are mainly *environmental issues* and the “colliding object” for these cases is *bird*. Also, the dominant “phase of flight” for these accidents and incidents is *cruise*.

- Factor 3: Organisation issues

This factor represents the cases where *organisations issues* is the “hazard category”. Most of the recorded cases that contribute to this factor are the ones that occurred due to the lack of coordination among multiple aerial operations. Detecting aircrafts, helicopters, parachutes landing, or other drones in the vicinity of the UAV flight path and terminating the operation is the common pattern for these cases.

- Factor 4: Colliding to static objects

Colliding to trees or other static objects is the primary “cause of occurrence” for the failures represented by this factor. Besides, *Loss of awareness* is also an important “cause of occurrence” for these failures.

- Factor 5: Equipment issues

This factor represents the occurrences that are caused by hardware issues, related to the electronical and/or mechanical components of the UAS.

# 5. Conclusion

This paper conducted a post-accident analysis on civil unmanned aircraft system accidents and incidents in Australia. First and foremost, this study is advocating for a comprehensive and consistent taxonomy with unique identifiers for each category to permit common coding in UAS accidents/incidents reporting. This is an essential prerequisite to targeted accident prevention, as the first step to rectify risk is recognizing its source.

The analysis of univariate and bivariate distributions of collisions’ attributes showed *equipment factor* is the “hazard category” for more than 60% of collisions. *Equipment factor* has mainly resulted in *loss of ground control (LGC)*, *navigation* problems, and *system component failure (SCF).* This is while there is no proper mechanism in place to monitor the airworthiness of UAVs. Also, nearly 80% of the collisions occur during the *cruise* phase of flight, which suggests that safety procedures for civil manned aircraft cannot be directly adopted for UAS due to the dissimilarities in their typical operation altitude.

In addition to analysing the attributes’ distributions, exploratory factor analysis (EFA) is utilised as a systematic approach to detect potential constructs behind the attributes. Based on the results, accidents and incidents can be divided into five categories of “loss of awareness”, “bird strike”, “organisation issues”, “colliding to static objects” and “equipment failures”. Current regulations around UAS is mainly concerned with “loss of awareness” and “colliding to static objects”. This paper suggests a comprehensive registration system which imposes regular safety inspections for UAVs can help to reduce the “equipment failures” accident and incident type. Moreover, to avoid the operation of UAVs interfering other aviation sectors, an integrated control system is required to help with coordinating UAVs’ operations and other sectors. Lastly, the regulations must consider environmental impacts of UAVs’ operations and impose restrictions where UAV can be a threat to the wildlife.

# Acknowledgment

We are grateful to Mr Noel Arnold for comments that greatly improved the manuscript.

# References


ATSB 2017. A safety analysis of remotely piloted aircraft systems. *A rapid growth and safety implications for traditional aviation. 2012 to 2016.* Australian Transport Safety Bureau

BARTHOLOMEW, D. J. 1980. Factor analysis for categorical data. *Journal of the Royal Statistical Society. Series B (Methodological)***,** 293-321.

BUREAU, A. T. S. 2017. A safety analysis of remotely piloted aircraft systems 2012 to 2016: A rapid growth and safety implications for traditional aviation. AR-2017-016, 9 August.

CICTT 2011. Aviation Occurrence Categories Definitions and Usage Notes. Commercial Aviation Safety CICTT, ICAO Common Taxonomy Team.

CLARKE, R. 2014. The regulation of civilian drones' impacts on behavioural privacy. *Computer Law & Security Review,* 30**,** 286-305.

COLOMINA, I. & MOLINA, P. 2014. Unmanned aerial systems for photogrammetry and remote sensing: A review. *ISPRS Journal of photogrammetry and remote sensing,* 92**,** 79-97.

D'ONFRO, J. 2014. NASA drone traffic management system: This NASA project is the best hope to stop a potential drone disaster. *Business Insider*.

DERUYCK, M., WYCKMANS, J., MARTENS, L. & JOSEPH, W. Emergency ad-hoc networks by using drone mounted base stations for a disaster scenario. 2016 IEEE 12th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob), 2016. IEEE, 1-7.

GETTINGER, D. 2017. Drones at home: Public safety drones. *Center for the Study of the Drone at Bard College. Retrieved from http://dronecenter. bard. edu/files/2017/04/CSD-Public-Safety-Drones-Web. pdf*.

HAM, Y., HAN, K. K., LIN, J. J. & GOLPARVAR-FARD, M. 2016. Visual monitoring of civil infrastructure systems via camera-equipped Unmanned Aerial Vehicles (UAVs): a review of related works. *Visualization in Engineering,* 4**,** 1.

HUBBARD, B., WANG, H., LEASURE, M., ROPP, T., LOFTON, T., HUBBARD, S. & LIN, S. Feasibility study of UAV use for RFID material tracking on construction sites. Proc., ASCE Annual International Conference, 2015. 669-676.

IRIZARRY, J., GHEISARI, M. & WALKER, B. N. 2012. Usability assessment of drone technology as safety inspection tools. *Journal of Information Technology in Construction (ITcon),* 17**,** 194-212.

IWATA, K. & MATSUMOTO, O. 2013. Research of Cargo UAV for civil transportation. *Journal of Unmanned System Technology,* 1**,** 89-93.

LEE, S. & CHOI, Y. 2016. Reviews of unmanned aerial vehicle (drone) technology trends and its applications in the mining industry. *Geosystem Engineering,* 19**,** 197-204.

LIU, P., CHEN, A. Y., HUANG, Y.-N., HAN, J.-Y., LAI, J.-S., KANG, S.-C., WU, T., WEN, M.-C. & TSAI, M. 2014. A review of rotorcraft unmanned aerial vehicle (UAV) developments and applications in civil engineering. *Smart Struct. Syst,* 13**,** 1065-1094.

LUPPICINI, R. & SO, A. 2016. A technoethical review of commercial drone use in the context of governance, ethics, and privacy. *Technology in Society,* 46**,** 109-119.

MÁTHÉ, K. & BUŞONIU, L. 2015. Vision and control for UAVs: A survey of general methods and of inexpensive platforms for infrastructure inspection. *Sensors,* 15**,** 14887-14916.

NEX, F. & REMONDINO, F. 2014. UAV for 3D mapping applications: a review. *Applied geomatics,* 6**,** 1-15.

PERRITT JR, H. H. & SPRAGUE, E. O. 2016. *Domesticating Drones: The technology, law, and economics of unmanned aircraft*, Routledge.

QUARITSCH, M., KRUGGL, K., WISCHOUNIG-STRUCL, D., BHATTACHARYA, S., SHAH, M. & RINNER, B. 2010. Networked UAVs as aerial sensor network for disaster management applications. *e & i Elektrotechnik und Informationstechnik,* 127**,** 56-63.

REVELLE, W. & ROCKLIN, T. 1979. Very simple structure: An alternative procedure for estimating the optimal number of interpretable factors. *Multivariate Behavioral Research,* 14**,** 403-414.

SACHS, G. 2016. Drones. Reporting for Work.

SHALIZI, C. 2013. Advanced data analysis from an elementary point of view. Citeseer.

TOKEKAR, P., VANDER HOOK, J., MULLA, D. & ISLER, V. 2016. Sensor planning for a symbiotic UAV and UGV system for precision agriculture. *IEEE Transactions on Robotics,* 32**,** 1498-1511.

TRYFOS, P. 1998. *Methods for business analysis and forecasting: text and cases*, Wiley.

ZHANG, C. & KOVACS, J. M. 2012. The application of small unmanned aerial systems for precision agriculture: a review. *Precision agriculture,* 13**,** 693-712.