RESILIENT STRATEGIES IN COMMERCIAL AVIATION

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When we fly and nothing scary happens, is the system's design affording this success? Not always — sometimes humans are the cause of success. This resilient performance is often overlooked. To capture this, we explore two types of *strategies*: *countermeasures* and *modifications*. First, *countermeasures* are behaviors triggered by variables anticipated to be challenging or problematic (*pressures*). To capture this, we look at examples of how a problem was avoided. For example, a country road may have a hairpin turn where accidents occur. With this *pressure* identified, we look at successful drivers for insights. *Modifications* are changes that are created to fill a gap between work-as-imagined and work-as-done. This *strategy* is from the design of systems. In aviation, work-as-imagined is often explicit, so it can be compared to behaviors using data. These two resilient potentials aim to better understand how systems function, as well as how people contribute to unrecognized successes.

Our understanding of how humans contribute to successes in aviation organizations is limited because we do not systematically investigate this area. One assumption is that when safety performance indicators do not exceed unacceptable thresholds, things are going as planned. However, this is sometimes not the case. Notably this is due to the capacity for humans to adapt and achieve goals despite being given poor tools. Hollnagel's 2011 "work-as-imagined" versus "work-as-done" concept provides us with the language to illustrate the gap where compensatory behavioral *strategies* exist that create the appearance of normality and mask contextual variables (*pressures*) that render the imagined work unfeasible.

The term *"pressures"* describes operational, environmental, or other forces that may be challenging and that may stress the resources of the individual (Blajev & Holbrook, 2022). We are using this terminology to help describe what is triggering the resilient performance of interest.

Although many behaviors exist that can enable resilient performance, two behavioral *strategies* that we posit help provide the appearance of normalcy in the face of *pressures* and that may indicate a need for organizational intervention are: *countermeasures* and *modifications.* A *countermeasure* is an action that sets a barrier or mitigation against an anticipated *pressure*; thus, increasing the likelihood of goal success (American Airlines' Department of Flight Safety, 2020). A *modification* describes the augmentation or change, specifically to a procedure or policy that also increases the likelihood of goal success. Although similar, the distinguishing factor between *countermeasures* and *modifications* is that *countermeasures* are heuristics deployed in a variety of situations. These may become *modifications* if a systemic issue is present, and the *countermeasure* has been adopted unofficially by users.

From an organizational perspective, these adaptive *strategies* and the *pressures* (i.e., context-dependent variables triggering them) are the targets of this methodology. Identification of *pressures* can help with redesigning systems aimed at expanding the range of work-as-imagined to include more of the total distribution. The goal is to enhance predictability by learning from one's own workforce. Our approach to this opportunity is to leverage existing concepts and data collection methods but alter the indicators of interest.

We acknowledge that many strategies that are preventative could be classified as *countermeasures. Modifications* are also essentially the same behavior as *countermeasures*, but related to a policy or procedure. Thus, *modifications* are specifically relevant to organizations and should not be used to classify the *strategies* themselves initially, as they are a sub-group. We suggest investigating when the goal of the *strategy* is similar to the basic goals of the organization. That is, when people are trying to ensure critical organizational functions are successful. If so, domain experts are necessary to make that determination.

This provides us with an opportunity for new learning. These issues are especially critical now since there is a push to make aviation autonomous where these strategies may need to be factored into autonomous operations. We are proposing an approach to capture these strategies by utilizing a variety of data sources that are currently in-use.

Human vs. organizational resilience. Humans are born with the abilities that are necessary to adapt and handle challenges; organizations however, are groups of people, systems, and are entities of their own. Even with resilient performers within the organization, the organization must deliberately design-in resilient potentials.

One method that organizations can use to begin is to develop the potential to *learn* from their naturally resilient human performers. We use the term *learn* as a potential for organizational resilient performance as described in Hollnagel's (2011) Resilience Assessment Grid (RAG). The organization must be able to introspect and understand how its systems and policies perform – at least to a level that is meaningful for their success.

Positive deviance. The concept of investigating what works is not new. Positive Deviance (PD) is the review and understanding of high performers in situations where challenges exist and has been around since the 1970s (Positive Deviance Collaborative, 2023). Identifying and understanding success cases from high performers follows a general process: 1) Differentiate high/low performers; 2) study what makes them perform differently; 3) test hypotheses (Bradley, et al., 2009). This methodology has been successful in environmental health and hospital care domains (Bradley, et al., 2009).

Resilient performance indicators. Safety has generally been defined in terms of its absence. This is noted by the generally negative theme of safety performance indicators (SPIs). For example, loss of separation, ground proximity warning, and bird strike are all examples of current SPIs (International Civil Aviation Organization, 2023). These events are important to measure, but are a small minority of the overall occurrences in the system (PARC/CAST, 2013). Therefore, we intend to start an analogous catalog of resilient performance indicators (RPIs). That is, a list of events that are deemed to be desired performance and not merely under the threshold of what is unacceptable.

To search for RPIs we can leverage the massive amounts of data generated by the aviation system. A variety of sources exist, which include: 1) Aircraft centric data such as Flight Operational Quality Assurance (FOQA) data that can be leveraged to determine how the aircraft was flown, 2) Surveillance data such as ADS-B or radar track data that reveals how multiple aircraft interact within air traffic patterns, and 3) text reports and narratives from NASA's Aviation Safety Reporting System (ASRS) or airline Aviation Safety Action Program (ASAP) that captures the context of the operations and why safety events mishaps happen. Other rich text narratives from the LIT or Line Operations Safety Audit (LOSA) offer additional insights into behaviors that capture the context from a different perspective. Indicators from these various data sets can be informative in determining what resilient behavior humans are performing to make the system run safely.

Resilient Performance may not be positive for everyone. Although resilient performance may be a positive indicator that people are essential to success, it can also highlight issues that need to be improved within an organization. If there are cases where users of a system feel compelled to to alter or augment it, there is likely a need for change. Organizations should embrace this as continual improvement for all stakeholders and not criticism.

Case Study 1. Wake Turbulence *Countermeasures*

Event Report Initiated Analysis (context rich – occurrence-rate poor)

Countermeasures can potentially be more generalizable than *modifications* and not tied to a particular procedure or policy. Thus, searching for these *strategies* can be initiated around observing operator actions as well as event reports. LOSA, ASRS, and ASAP may trigger an investigation into the objective data such as FOQA to quantify the occurrence rate. This is achieved by running a targeted search within the numerical data to detect points in the flight that match a SME's query parameters. When undesirable events are identified, mitigating strategies can then be crafted and implemented. Subsequently, the numerical data can be monitored to measure whether the mitigations are working. With this well-established methodology already in practice, it can be reversed to capture successful operations as well.

Step 1. Identify the *strategy* occurrence in operations

Example: We used flight deck observation data collected during a simulated series of flights at NASA Langley Research Center (Stephens et al., 2021). The observations were a subset of two crews' data (Stewart, et al, 2023). When pilots are managing wake turbulence events on arrival, they may request speed relief to increase distance from the previous aircraft. Another strategy was a request for lateral offset on the arrival to avoid the turbulence altogether (See Table 1.).

Proficiency	Pressure	Description	Goal	Outcome	Description
Countermeasures	ATC/ Traffic	Asked ATC for 1 mile offset to avoid wake	Avoid wake turb	Success	No wake was observed
Countermeasures	ATC/ Traffic	Asked ATC to slow for additional spacing for A330	Avoid wake turb	Failed	Hit wake

Table 1. Observation examples of countermeasures used to avoid a wake turbulence event.

Step 2. Identify contextual *pressure* variables

Example: *Pressures* that may trigger a *countermeasure* response could be due to high traffic flow which results in reduced spacing when following a heavy aircraft on arrival. Recommended spacing behind a heavy is 7 NM for large and 8 NM for small aircraft. Thus, ATC and traffic were both coded as *pressures.*

ASRS Report 1. "*SOCAL Approach Control cleared our flight for the ILS 24R via the CRCUS transition. We were following a B787-9. To help increase the space between our airplanes the Los Angeles Center Controller instructed us to slow to 250 KIAS while on the ANJLL4 arrival which we complied with. Looking at our TCAS display, I estimated the 787 was approximately 5 miles ahead of us. SOCAL approach appropriately cautioned us for wake turbulence since we were following the heavy 787. Our flight was normal until we reached CRCUS waypoint where we encountered the 787's wake".*

In this scenario the reduced traffic spacing was anticipated as a *pressure* that would result in wake turbulence. A *countermeasure* to reduce speed was applied, however the desired spacing was not achieved and wake turbulence was encountered.

Step 3. Compare outcomes with and without *strategy*

Example: This step is key to having all data sources available to properly assess the outcome. FOQA data can objectively determine how the wake turbulence event is managed, while radar track data can provide the distance and aircraft type of the proceeding aircraft. Being able to fuse these data sources together would facilitate an assessment of whether the *strategy* was successful or not and what *pressures* were involved either internally or external to the aircraft.

Outcome. This example does not have a real-world outcome as it used simulated observation data. However, this methodology could be employed if enough observational data are collected, and a consensus is reach on the efficacy of the *countermeasure.*

Descriptions of countermeasures and modifications can be found that address and resolve the safety issue being reported. Evidence of these actions may be present in the numerical data during these adverse situations. It is also possible to determine if these countermeasures are being implemented in consistent geographical locations, which may indicate a hot spot where positive deviations are necessary. This approach can provide insight into commonly used strategies to handle adverse situations. Furthermore, the intervening actions that are implemented can be examined to determine if they are safe strategies or if a systemic change is needed to address the problem in the system that is requiring positive deviations by the operators in the first place.

Case Study 2. DFW Arrival *Modification*

Numerically Initiated Analysis (occurrence-rate rich – context poor)

To identify *modifications,* we examine -work-as-imagined (WAI) versus work-as-done (WAD). Examples of WAI are procedures, which are used in many aspects of aviation. This case study is a standard terminal arrival route (STAR) serving Dallas Fort Worth International Airport (DFW). By comparing the vertical confines of the procedure with radar tracks of aircraft that flew the lateral confines, we can see when adherence to the criteria of the procedure is, or is not, occurring. This was accomplished using a system called RADI (Stewart, Matthews, 2017). This may require a positive deviation from work imagined to achieve the high- level goal. While the work imagined of the procedures is to automate the arrival to facilitate lower workloads for air traffic controllers (ATC) and provide optimal profile descents to save on fuel, this is not always achievable due to compounding factors such as weather, high or low traffic loads. Knowing what the procedure restrictions are, we can look for systemic areas where adherence is low or if flights are missing restrictions by a consistent margin. This can point to possible modification techniques that air traffic controllersATC use to re-route traffic to meet the higher-level objective of flights reaching their destination safely. Once a systemic non-adherence is identified, the location or waypoint fix can be searched for in ASRS to help ascertain why a restriction was not met.

Step 1. Identify Systematic Difference Between Work-as-Imagined and Work-as-Done.

Example: Altitudes not being adhered to on BOOVE arrival procedure into KDFW: Crossing DELMO waypoint at 12,000ft and 10,000ft instead of the published 11,000ft.

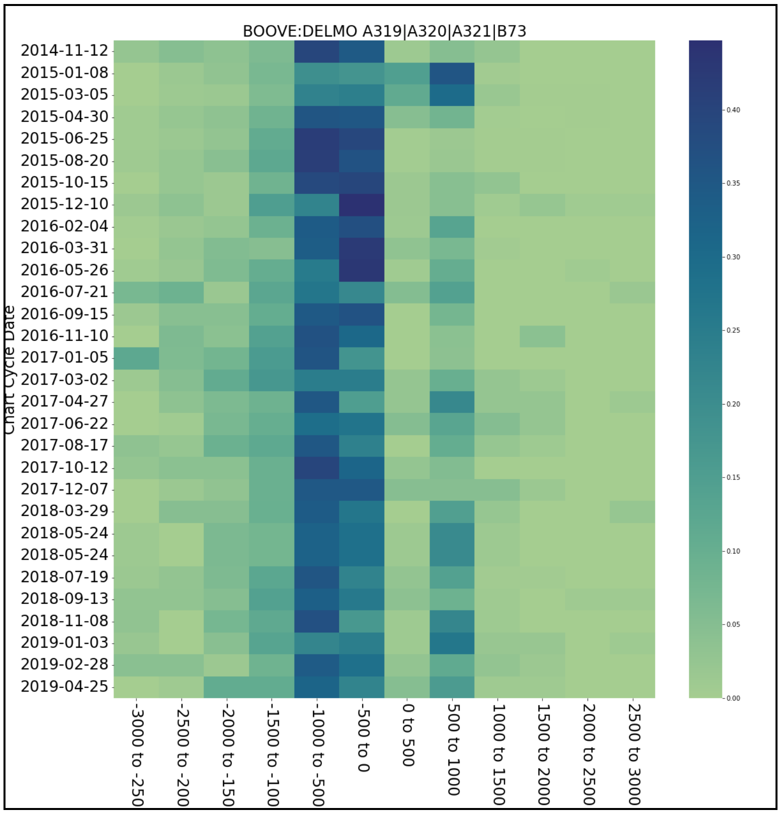

Figure 1. Proportions of altitude crossings relative to the restriction altitude at waypoint DELMO over time.

Step 2. Identify contextual *pressure* variables

Example: Look at subjective event reports (ASRS, ASAP, and company specific) for context clues and search based on commonalities or fusion points. This case would be the arrival (BOOVE) and the waypoint (DELMO).

ASRS Report 1. *"During the BOOVE4 arrival into DFW. We were descending out of 11400 just prior to DELMO for 11000. Approach advised us of traffic at our 1 o'clock climbing. Seconds after, we had a traffic advisory from the TCAS that immediately changed to an RA with a climb advisory.* ***Traffic alerts from ATC and TCAS into DFW occur on almost every arrival and departure.****"*

After identifying a candidate *pressure* – traffic in this case, we could determine that there is likely a *pressure* and that a *modification* is being used to manage that *pressure*.

Step 3. Attempt to determine if the *modification* is successful at creating higher performance.

Example: For this portion of the example, we would need to have access to the airline's internal data sources. In this case, FOQA data for TCAS Resolution Advisories would be the target variable.

Outcome. In this example, the waypoint DELMO was changed in the procedure from 11,000ft to 12,000ft. This structural change to the procedure illustrates that the *modification* may have been necessary and was included in the subsequent BOOVE6 iteration of the procedure (see Figure 2.).

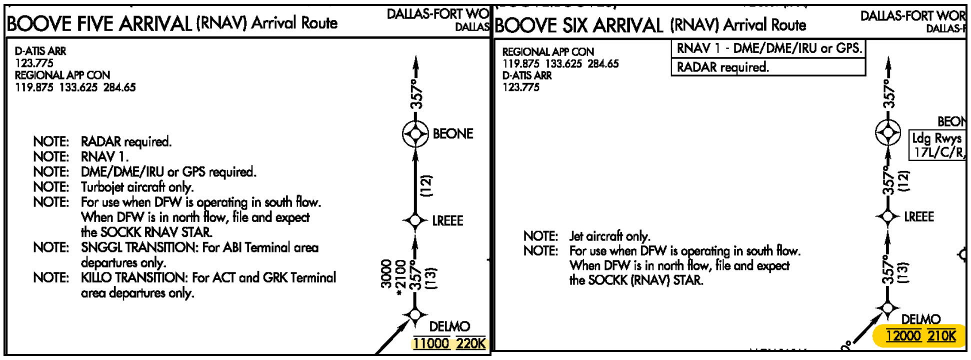

Figure 2. Navigation chart depicting the change to the procedure altitude.

Conclusion

We described a general process using currently available safety data that can be used to capture two different resilient performance *strategies*: *countermeasures* and *modifications.* Investigating the effectiveness, and how these *strategies* are used to counter *pressures* may help to identify systems that are not functioning as intended, while simultaneously offering possible solutions. This approach should be tested and further developed to maximize its operational value. Our next steps are to provide empirically validated results using real-world data. When these solutions are captured, understood, and built into an organization, it has an increased potential to learn and adapt as things naturally change.

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