

Optimisation of key performance measures in air cargo demand management

Authors:

Alexander May¹
Adrian Anslow²
Udechukwu Ojiako³
Yue Wu¹
Alasdair Marshall¹
Maxwell Chipulu^{1,3}

Affiliations:

¹School of Management,
University of Southampton,
United Kingdom

²Revenue Management
and Pricing Analytics, Virgin
Atlantic Cargo, United
Kingdom

³Faculty of Management,
University of Johannesburg,
South Africa

Correspondence to:

Udi Ojiako

Email:

uojako@uj.ac.za

Postal address:

PO Box 524, Auckland Park
2006, South Africa

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This article sought to facilitate the optimisation of key performance measures utilised for demand management in air cargo operations. The focus was on the Revenue Management team at Virgin Atlantic Cargo and a fuzzy group decision-making method was used. Utilising intelligent fuzzy multi-criteria methods, the authors generated a ranking order of ten key outcome-based performance indicators for Virgin Atlantic air cargo Revenue Management. The result of this industry-driven study showed that for Air Cargo Revenue Management, 'Network Optimisation' represents a critical outcome-based performance indicator. This collaborative study contributes to existing logistics management literature, especially in the area of Revenue Management, and it seeks to enhance Revenue Management practice. It also provides a platform for Air Cargo operators seeking to improve reliability values for their key performance indicators as a means of enhancing operational monitoring power.

Introduction

The air cargo industry is one of the fastest-growing sectors of transportation (Wong *et al.* 2009). Boeing (Hpanchal 2011) has projected that global demand in air cargo operations may rise as much as 5.9% per annum until 2029. A select number of scholars, such as Slager and Kapteijns (2004) and Becker and Wald (2010), emphasised the value of Revenue Management for such operations, particularly in the current era of globalised and deregulated competition.

Capacity demand for air cargo operations is measured in terms of two primary dimensions: volume or size, and weight. Generally, such demand is articulated up-front by freight companies through an open-bidding system, in an operational process described in greater detail by Bish, Suwandechochai and Bish (2004) and Popescu *et al.* (2006). This bidding process for cargo capacity is dominated by a small number of large freight forwarding companies (Slager & Kapteijns 2004). Their commercial power ensures that they do not pay for any unused capacity that they have reserved (Amaruchkul *et al.* 2011). Hence, airlines wholly own the risks associated with 'no-shows'. This unanticipated spoilage is an opportunity cost (Moussawi-Haidar & Cakanyildirim 2012; Li, Bookbinder & Elhedhli 2012), which is measurable by loss of revenue for each kilogram of unused capacity (Pak & Dekker 2004). Airlines therefore overbook based on spoilage estimates (Becker & Wald 2010; Moussawi-Haidar & Cakanyildirim 2012).

Cargo capacity is invariably perishable, in the sense that unused hold space is lost once a flight departs. This may not always be remediable when flights load and unload at stopovers en route to final destinations (Billings *et al.* 2003). The primary focus of air cargo Revenue Management (ACRM) is therefore to optimally match capacity to demand, both before each journey and within journeys between stopovers. Freight forwarders need to be targeted with the correct, individualised product, at the right time (perhaps as an aircraft is en route between stopovers), through the best channels, and at a price that will be both low enough to be predictive of success in filling capacity and high enough to earn good revenue. Of course, considerable forecasting challenges arise here. An important complicating factor is that the product itself (capacity) is multidimensional. Cargo is defined not only by volume or size and weight, but also in terms of its compatibility with unit load devices (individual pallets or containers that bundle and secure cargo on the aircraft) and by its position in the cargo hold (weight distributions must be balanced across cargo holds to maintain aircraft stability) (Amaruchkul & Lorchirachoonkul 2011). Capacity demand can also be subject to severe and unanticipated fluctuations caused by changing quantities and types of cargo, which can surprise the freight-forwarders (Bartodziej *et al.* 2007; Teunter & Duncan 2009). The limited availability and questionable relevance of historical data therefore continually hamper the forecasting efforts of revenue managers (Chou *et al.* 2010).

Despite evidence suggesting that some cargo carriers, such as American Airlines (Smith, Leimkuhler & Darrow 1992) and KLM (Slager & Kapteijns 2004), have successfully used Revenue

Management to balance demand and supply (thus increasing profits), these success stories do not seem to provide generalisable learning examples (Queenan *et al.* 2009). An important consideration here is that Revenue Management, although very commonly associated with the airline industry since BOAC experimented with it in the 1960s and American Airlines started calling it 'yield management' in the 1970s (McGill & Van Ryzin 1999), has made far greater inroads into the passenger airline industry than into the dimensionally more-complex air cargo industry (Becker & Dill 2007).

Academic literature on Revenue Management in the airline industry also reflects a number of different developmental levels relating to performance measurement. Scholars, such as Tung, Baird and Schoch (2011), have suggested that issues arising from this, which are well understood, include: the need to review indicators based on what their unanticipated behavioural consequences turn out to be, and bias arising from managers who are motivated by professional-performance evaluation preferring to embrace poor indicators that show good performance as opposed to good indicators that show poor performance (Simon *et al.* 1954; Ridgway 1956). As yet, few, if any, academic studies of performance measurement have evaluated ACRM practice from this very demanding standpoint. Yet, there is a clear need for such literature. It ought to be of great interest to air cargo operators, such as Virgin Atlantic Cargo, who are keen to optimise operational decisions in the light of ever-increasing (globalised and deregulated) market competition (Sabre 2009).

This present study sought to address two major objectives. The first was to fill the observed gaps in academic literature. The second, and what this study was expressly commissioned to do, was to provide recommendations to Virgin Atlantic Cargo on how to optimally achieve effective monitoring of operational decisions. To meet these objectives, the authors sought to: establish the most effective (and not necessarily the best) key performance indicators (KPI) of Revenue Management (RM), as applied to the areas of Route Management, Capacity Control and Inventory Management; and identify the methods and processes that would be required to accurately measure decisional performance against KPI indices. To support the attainment of these aims, this article is structured in the following order: an overview of Revenue Management literature and Revenue Management operations in Virgin Atlantic Cargo; key operational performance indicators; research methodology; results; conclusions.

Revenue Management

Revenue Management principles

Drawing from the earlier work of Pak and Dekker (2004), Revenue Management can be defined as the practice of selecting specific functionalities in order to optimise maximum revenue from a fixed and perishable capacity. However, Talluri and Van Ryzin (2005) suggested that whilst the problems of Revenue Management are as old as business itself, advances in scholarship have enabled it to become

an optimised approach to demand-management decision making. Generally, the *effectiveness* of cargo carrier Revenue Management decision-making can be captured in two core metrics: (1) load factor (comprising volume load and weight load). The effect of the overbooking level decisions can be determined from flight load factor. This is calculated on departure, as the proportion of available capacity consumed by cargo volume and weight dimensions. (2) Gross yield, which measures cargo-operation productiveness in terms of revenue generated per tonne-kilometre or tonne-mile.

To optimise Revenue Management, scholars such as Bartodziej *et al.* (2007) have presented a mathematical programming approach based on routing, which integrates Revenue Management with structural decisions and capacity allocations. This is undertaken using a modified version of a multi-commodity network flow model previously developed to support schedule-planning decisions in cargo airlines. This programming approach aims to provide airlines with an element of flexibility, which enhances their ability to respond to requests for shipment bookings. This allows for different schedules to be planned for the network within the constraints of both origin-destination and delivery time.

In a study by Vinod and Narayan (2008), a nonlinear rate-optimisation model designed to overcome problems associated with quantity discounts (based on both weight and volume of shipments) was presented. However, a key constraint of their model is that it uses estimated demand elasticity (the change in demand with respect to the change in price) to determine optimal rates. Huang and Chang (2010), on the other hand, presented an approximation algorithm for an expected revenue function with a dynamic programming model, which takes into account the stochastic volume and weight of shipments. Their solution is based on optimised Revenue Management, which is calculated as follows: for each time period t , given the accumulated weight y and the accumulated volume x , a booking request of type i will be accepted if its revenue is greater than the expected revenue decrease (the opportunity cost) due to the state change at period $(t-1)$.

Another study of interest is that of Xiao and Yang (2010) who formulated a continuous-time stochastic control model in order to derive the optimal solution to a Revenue Management problem for products with two-capacity dimensions (this includes air cargo, which has three dimensions: volume, weight and container position). They noted a relationship between multi-dimensional Revenue Management problems and categories of network Revenue Management problems. Under such conditions, each leg in an itinerary on an n -leg route is considered as an additional capacity dimension that equals '0' or '1'. This arises whenever customers request products that may include capacity resource bundles. Xiao and Yang's model also assumes Poisson demand streams, which are independent. These demand streams have different capacity requirements of M and N units occurring over a time horizon within the interval $[0, T]$ and at the point (t, m, n) . A demand-control policy is selected from a number of options,

which leads onto the next stage of inventory and time. Most importantly, they showed that the optimal policy for control of multi-dimensional inventory does not necessarily control demand flows solely on price. Thus, Xiao and Yang's model suggests that the expected marginal value of capacity will decrease over time. Thus, the threshold-type control favours demand requests, which lead to more balanced capacities.

Overview of Virgin Atlantic Cargo

Virgin Atlantic Airways is the UK's second largest long-haul airline. Its fleet consists of combination passenger-cargo aircraft, including thirteen Boeing B747-400s, four Airbus A340-300s, nineteen Airbus A340-600s and two Airbus A330-300s.

Virgin Atlantic's cargo handling operations are run through Virgin Atlantic Cargo, with cargo-handling facilities primarily located at four major United Kingdom airports: London Heathrow, London Gatwick, Manchester and Glasgow. The company operates long-haul cargo freight services from three major hubs including: London Heathrow (to Accra, Boston, Cape Town, Delhi, Dubai, Hong Kong, Johannesburg, Lagos, Los Angeles, Miami, Mumbai, Nairobi, New York (JFK and Newark), San Francisco, Shanghai, Sydney, Tokyo, Vancouver and Washington); London Gatwick (to Antigua, Barbados, Cancun, Grenada, Havana, Las Vegas, Montego Bay, Orlando, St. Lucia and Tobago); and Manchester (to Barbados, Las Vegas and Orlando). Virgin Atlantic Cargo (Virgin Atlantic Cargo n.d.) also manages cargo services on behalf of other airlines such as Virgin Australia.

Virgin Atlantic Cargo's operational model

The Revenue Management team manages the capacity optimisation element of Virgin Atlantic Cargo. The team is also responsible for market knowledge and analytical capability support. One of the most important parameters underpinning Virgin Atlantic Cargo's operations is flight capacity. For the Revenue Management team, this involves servicing, with a sufficient number of unit load devices over a 14-day booking window, in order to maximise revenue.

Virgin Atlantic Cargo's operational model is similar to that of KLM Cargo (as described in much detail by Slager and Kapteijns 2004), whereby Route Managers within each network cluster (Europe, Americas, Asia-Pacific and the Middle East and Africa) adjust bid prices on a daily (or sometimes more frequent) basis. When capacity exceeds forecast demand, bid price is generally set at 'zero pence ++'. Often, only surcharges apply, where the revenue will cover only the variable operating costs. Otherwise, the bid price will be increased as demand increases, as a means of maximising revenue. To facilitate this process, a demand forecast may be constructed from historic booking profiles, for example, describing the cargo mix for a flight in terms of commodity type or proportions of free-sale or allocations.

Revenue Management operations within Virgin Atlantic Cargo

Revenue Management at Virgin Atlantic Cargo consists of three interrelated discipline areas: Route Management; Capacity Control; Inventory Management, with Systems Development providing analytical support to all three discipline areas. More specifically, Route Management is responsible for capacity access management across all Virgin Atlantic Cargo routes.

The role of Capacity Control is to prioritise cargo shipments and serve as a contact point for Virgin Atlantic Cargo's global sales and operations teams. Capacity Control is also responsible for managing flight configuration and liaising with warehouses' operational teams during cargo shipment tenders, pallet building and container consolidation. The third interrelated discipline area within Virgin Atlantic Cargo is Inventory Management. This seeks to ensure that each station at the airport used by the network has sufficient on-hand container inventory to meet booked demand. In Virgin Atlantic Cargo, structural decisions (relating to sales formats and terms offered, including bulk discounts) are negotiated between route managers and their routes' sales account managers. Route managers make the medium-term quantity decisions (which allocate capacity to different market segments or products) in the form of overbooking limits, whilst Capacity Control makes short-term quantity decisions relating to the shipments.

Specifying and prioritising key performance indicators

Key performance indicators

Key performance indicators (KPI) have long been a topic of considerable interest in accounting (Simon *et al.* 1954; Ridgway 1956; Demski 1969), project and operations management (Tung *et al.* 2011) and supply chain management (Chan & Qi 2003; Shepherd & Gunter 2006) research literature. Generally, KPIs may tap both processes (behaviours) and outcomes (results). Literature about behavioural KPIs (Simon *et al.* 1954; Ridgway 1956; Litzky, Eddleston & Kidder 2006) has emphasised that the behaviours that most influence outcomes can easily be missed or downplayed. The possibility that managers may do this for some of their own behaviours is an issue that has already been raised (Litzky *et al.* 2006; Franco-Santos & Bourne 2009). Another is that behaviours are generally challenging to measure because observer viewpoints can introduce subjectivity and conceptual vagueness (Bourne *et al.* 2000; Franco-Santos & Bourne 2009). This may be especially true where a KPI's purpose is to improve behaviour towards greater conformity to abstract strategic objectives. In such cases, desired behavioural improvements may only become assessable or realisable after a considerable number of years (Batista 2012).

Key performance indicators that monitor and seek to improve outcomes, on the other hand, are generally framed in terms of measurable outcomes (Latham 2004; Locke 2004).

Forms of quantification that rely minimally or not at all upon subjective judgment are hallmarks of this design approach (Hanson, Melnyk & Calantone 2011; Tung *et al.* 2011). This means that outcome-based KPIs can be well suited towards operational assessments of performance, wherever 'management by objectives' exists in an organisation. Bourne *et al.* (2000) and Franco-Santos and Bourne (2009), identified outcome-based KPIs to include sales revenues (of which Revenue Management is a constituent element). The present study scrutinises outcome-based (rather than behavioural) KPIs that are designed to link to the revenue outcomes that ultimately matter the most. It must be emphasised that no matter what sort of KPI is being dealt with, unintended behavioural consequences may result from its use; the consequences may be unmeasured. Indicator review processes followed by practitioners and academics alike, therefore, cannot claim thoroughness without vigilance towards possible positive and negative behavioural effects. It is suggested that such vigilance must be proactive and exploratory, in the sense that it must look far beyond what gets measured to find the facts and build theories.

Outcome based key performance indicators

Revenue Management practitioners often select outcome-based KPIs following benchmarking exercises. This can invite narrow, one-dimensional thinking that fails to explore correlations and trade-offs between measures (Min & Joo 2006). In fact, Shepherd and Gunter (2006) maintained that most available decision-models do not precisely define the cause-effect relationships that underlie such correlations, and out of which the need for trade-offs can arise. Such problems have intensified, as dynamic KPI models have replaced static ones. In older and more static models, parameters were generally set at the onset of the modelling and have remained constant. On the other hand, the dynamic models that are emerging from the performance-measurement revolution increasingly rely on fuzzy performance parameters or indices. Arguments for prioritising some measures over others can therefore be very hard to construct.

Research methodology

Key performance indicator specification

Based on advice from Revenue Management specialists at Virgin Atlantic Cargo, a set of ten outcome-based KPIs were identified during the course of this study. Table 1 shows the specification for each KPI.

One of the outcome-based KPIs that were identified by Virgin Atlantic Cargo as being of interest, was *Optimising Density*. One of the required data fields for the *Optimising Density* KPI is Inverse Density, which requires non-valid values to be *Winsorised* with reference to standard density (Hasings, Mosteller, Tukey & Winsor 1947; Dixon 1960). *Winsorising* is required for valid outliers where their corresponding z -score > 3 is replaced by $\mu + (\sigma*3)$. K -means clustering is performed where $k = 5$; this is shown in Figure 1.

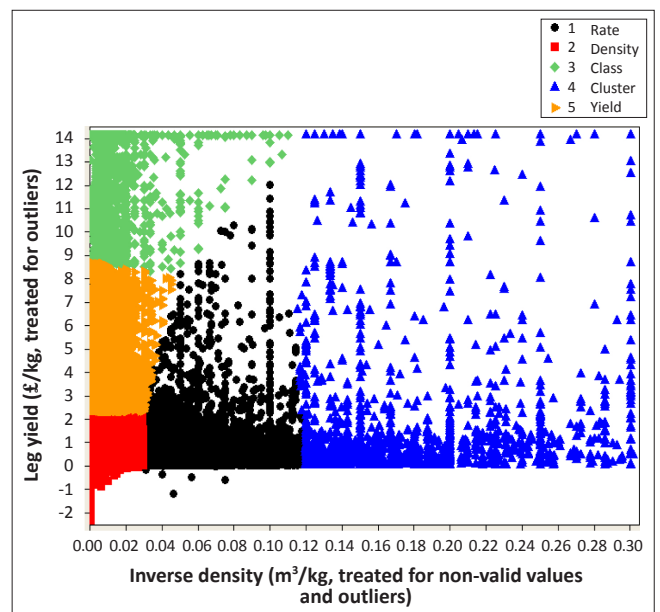


FIGURE 1: Scatterplot showing k -means clustering for rate density classes.

TABLE 1: Key performance indicator specifications.

Key performance indicator	Aim	Example of required data fields from <i>CargoMax</i> system	Analytical format (time series)
Utilisation for permanent bookings	Monitors compliance with acceptable cost levels for rate of show-ups or behaviour for each allocation for permanent bookings.	Recurring booking indicator, flight number and booked chargeable weight, actual (booked) weight, booked pieces, total pieces.	Percentages
Permanent bookings or free-sale mix	Monitors compliance of the permanent bookings to the optimally-determined proportion.	Free-sale or allotment indicator, booked volume and load factor free-sale.	Deviation
Overbooking	Monitors compliance of the actual to optimal overbooking levels.	Weight override, volume override, itinerary cancel reason.	
Network optimisation	Monitors compliance with the optimal cargo mix.	Origin station city code, destination station city code, leg or segment, agent code and agent name.	Average value of shipment
Optimising density	Monitors compliance of the actual to optimal proportions of rate density classes.	Booked volume, actual (booked) weight.	Deviation
Dynamic bid price	Monitors compliance of actual to optimal bid prices.	Volume historic bid price, actual volume, booked chargeable weight.	
Flight plan released	Monitors compliance of the actual to target percentage of flight plans released within the specified window.	Those relating to booking list completion.	Proportions
Flight plan audit	Monitors compliance with acceptable ratios rescheduled shipments.	Freight rate, chargeable weight, and free-sale or allotment.	Deviation
Empty equipment moves and maintaining station budgets	Monitors compliance of empty unit load device moves with the forecast amount.	Unit load device station counts, demand segmented, unit load device type and unit load device code.	

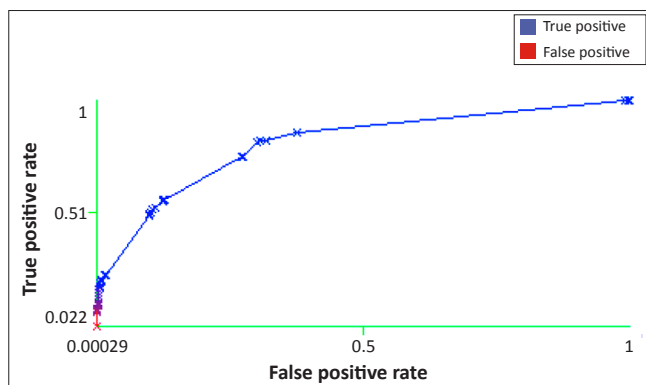
Modelling performance indicators

Popova and Sharpanskykh (2010) presented an approach to modelling performance indicators (PIs) based on formal modelling language. However, although this approach could be used in isolation to prioritise KPIs at Virgin Atlantic Cargo, the present study undertook an additional mapping exercise. The objective of the mapping being to not only build a provisional structure for the performance indicators, but also to establish interrelationships between indicators, based on what is theorised as relevance to corporate Revenue Management goals. Popova and Sharpanskykh's approach has identifiable strengths, in that once identified, the relationships between performance indicators (such as aggregation, positive and negative causation) would suggest a logical hierarchy relating to an organisation's goals. This approach also has identifiable disadvantages: the main one is that such hierarchies are hard to explain and justify. It is not always possible to establish mathematical or logical relationships between performance indicators and their underlying data fields. For example, an exploratory data-mining analysis of overbooked flights shown in Figure 2 achieved an accuracy ratio of 0.62.

In addition, the mapping exercises that might be undertaken here can be extremely time consuming. Note that the size of the resulting tree is 95, with 48 leaves, which rules out parsimonious use of theoretical narratives to interpret relationships between data fields. Also, since the input required would not necessarily lead to proportional results, there is a risk that the structure could only be partially completed. A similar argument can be made for the 'quantitative relationship at the performance measurement system' methodology presented by Rodriguez, Saiz and Bas (2009) in which KPI cause-effect maps were constructed to quantify objective relationships between KPIs in order to determine their importance for a performance-measurement system.

Model selection

In this present study, the intelligent, fuzzy multi-criteria group decision-making (FMCGDM) methodology developed by Lu, Zhang, Ruan and Wu (2007) was selected as the preferred modelling approach, but not before other fuzzy decision-making methods were also considered in detail.



Note: Plot (area under ROC = 0.8081); Accuracy Ratio = $2*(0.8081-1) = 0.62$.

FIGURE 2: Overbooked flights data fields classification.

A later fuzzy group decision-making model for multiple criteria developed by Anisseh and Yusuff (2011) based on a Borda count was initially considered. One advantage of the Anisseh and Yusuff model is its computational simplicity. The main difference from Lu *et al.*'s (2007) approach is that instead of each decision maker being required to complete a pairwise comparison of assessment criteria, all that is required is for each decision maker to select a weight for each criterion. However, in the absence of readily available software, the trade-off against Lu *et al.*'s (2007) model at the criteria weighting stage did not provide sufficient justification for adoption of this model, given the earlier cited accuracy constraints associated with this study.

Yeh and Chang (2009) developed another model, which was considered. Their model, in particular, demonstrates how the utilisation of a FMCGDM algorithm may be applied to larger-sized problems, by taking into consideration the relative importance of distances from both negative and positive ideal solutions (using weights), thus extending the degree of optimality concept. A cognitively prohibitive number of pairwise comparisons between criteria for the decision makers are avoided through the utilisation of Yeh and Chang's model. At the same time, individual absolute judgements were aggregated as a rating for group performance against each alternative. This was undertaken utilising a single, triangular fuzzy number as opposed to using fuzzy numbers (for individual judgements, as is normally the case in traditional approaches). However, in addition to this, decision makers utilising Yeh and Chang's model must also conduct pairwise comparisons to determine weights for groups of criteria and weights for the super-criteria to which these groups belong. Thus, whilst the approach appears to be a robust and effective method for improving the scalability of FMCGDM applications, the cognitive demands for decision makers using this method for smaller problems, such as the one faced by Virgin Atlantic Cargo with five criteria, do not appear to be any lower than under Lu *et al.*'s methodology.

Overall, the analysis suggests that mode by Lu *et al.* (2007) has two clear strengths over other models that were reviewed. In the first place, they incorporate analytic hierarchy process (AHP), which allows an intuitive understanding of a complex problem to be formalised as an attribute hierarchy. This is done at the individual preference generation stage for comparison of criteria using linguistic terms represented by fuzzy numbers. By contrast, other models such as Yeh and Chang (2009) include efficient aggregation of individual assessments replacing AHP with a hierarchical weighting procedure, which is more likely to be of benefit only in situations with large numbers of criteria and decision makers. Another advantage of the Lu *et al.* model is that it is quick to implement. For example, it requires only two matrices for the input of preferences.

To conclude, whilst acknowledging the sophistication of more recent approaches in FMCGDM that focus on addressing limitations with interdependent (Ramik & Perzina 2010), non-commensurable (Park *et al.* 2011), incomplete preferences (Xu 2010) and interval-valued intuitionistic fuzzy information (Xu & Yager 2009), the strengths of

TABLE 2: Assessment criteria definitions.

Criterion	Name	Definition
1	Impact of overall revenue	The degree to which the key performance indicators provide a description of activities that directly impact upon the creation of revenue.
2	Revenue per shipment-leg	The degree to which key performance indicators are seen to be important towards the articulation of the performance of selected cargo. This is generally based on what is expected in terms of revenue generation and outcome revenue profiles for planned shipments.
3	Optimised yield mix per flight-leg	The degree to which the key performance indicators demonstrate the effectiveness of decisions to either accept or reject decisions relating to the improvement of average yield emanating from a particular shipment.
4	Ease of influencing, effort ratio	A decision that is based on both tacit and explicit business information and intelligence on actions that is likely to lead to the production of a measureable impact upon the key performance indicators.
5	Ease of implementing Operational Research model support	The extent to which the key performance indicators demonstrate information completeness.

Lu *et al.*'s (2007) approach was in its simplicity in data collection, analysis and interpretation.

Fuzzy multi-criteria decision-making prioritisation of key performance indicators

The second objective of the study was to provide recommendations to Virgin Atlantic Cargo as to how to optimally achieve effective monitoring of operational decisions. This objective leads to subjective opinion being tested against objective reality. It implies that not only should the most valued KPI be identified from within the set of ten highlighted outcome-based KPIs, but also that separate consideration must be given to whether the assessor has exercised good judgment by focusing on the KPI that offers the greatest utility for revenue-maximising cargo decisions.

Whilst an ordinal ranking of KPIs would enable a most-valued subset to be identified (for example, the top three KPIs), a ranking order over a continuous interval was considered to be more likely to facilitate useful prioritisation, based on corresponding closeness or distance to a positive-ideal solution. Work by Lu *et al.* (2007, 2008) on 'intelligent' fuzzy multi-criteria group decision-making is relevant here. In particular, this work generated a ranking order of alternatives, in which the critical issues for the decision problem correspond to the top N highest values calculated for the closeness coefficients.

Multi-criteria decision making (MCDM) can be applied in a decision situation to allow a preference decision, based on evaluation, prioritisation and selection, to be made over a set of predetermined m alternatives (in this case, the ten KPIs) that are characterised by multiple, often conflicting attributes that correspond to a set of n criteria. According to Lu *et al.* (2007, 2008), a typical multi-criteria decision problem can be represented mathematically as follows:

$$(\text{MCDM}) \left\{ \begin{array}{l} \text{Select: } A_1, A_2, \dots, A_m \\ \text{subject to: } C_1, C_2, \dots, C_n \end{array} \right\} \quad [\text{Eqn 1}]$$

Where the *select* is based on maximising a multi-criteria utility function elicited from a group of decision makers represented by the set P_k ($k = 1, 2, \dots, n$). In this case, the information inputs to the model are expressed in the matrices D and W , and are shown mathematically as:

$$D = \begin{matrix} & C_1 & C_2 & \dots & C_n \\ \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_m \end{matrix} & \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \end{matrix} \quad [\text{Eqn 2}]$$

$$W = [w_1 \quad w_2 \quad \dots \quad w_n] \quad [\text{Eqn 3}]$$

Where x_{ij} , $i = 1, \dots, m$, $j = 1, \dots, n$, is the alternative A_i rating in relation to criterion C_j and w_j is the weighting of criterion C_j .

The criteria used in deciding the relative priority of the ten outcome-based KPIs for their objective utility in driving revenue-management performance are shown in Table 2. Because this was a commissioned study, the choice of the five criteria was made based on advice from Virgin Atlantic Cargo Revenue Management specialists working on the KPI project.

The data consisting of linguistic terms selected from fixed scales and were collected using a 'KPIs assessment tool' using Excel software (Microsoft, USA) in which an attempt was made to replicate the decision preferences input matrices of Revenue Management specialists in Virgin Atlantic Cargo against Step 3 of Lu *et al.*'s (2007) fuzzy decision support system. The set P_k ($k = 1, 2, 3$) was collated and then directly entered into the fuzzy decision support system¹. This was in order to enable the group aggregation to be computed according to the properties of fuzzy numbers (Step 4 of Lu *et al.* 2007).

Lu *et al.* (2007, 2008), defined a fuzzy number \tilde{a} as fuzzy set on \mathbb{R} , where $F(\mathbb{R})$ is the set of all fuzzy numbers on \mathbb{R} given below, which satisfies three conditions:

$$\tilde{a} = U_{\alpha \in [0,1]} \alpha [a_{\alpha}^L, a_{\alpha}^R], \text{ for every } \alpha \in F(\mathbb{R}) \quad [\text{Eqn 4}]$$

Where:

\tilde{a} is normal, that is, there exists an element $x_0 \in \mathbb{R}$ whose membership grade defines it as a full member of the set by the height of μ , such that $\mu_{\tilde{a}}(x_0) = 1$; the alpha cuts at $[a_{\alpha}^L, a_{\alpha}^R]$ are made on a closed interval such that every $\alpha \in [0,1]$; and the support of \tilde{a} is bounded, that is, let $F(\mathbb{R})$ be the set of all fuzzy numbers on \mathbb{R} then a real number $\lambda \in \mathbb{R}$ belonging to a crisp set can be defined on a fuzzy set such that $\lambda \in F(\mathbb{R})$ under the following membership function:

¹This is after the criteria had been entered in Step 1 and the weights set for the group members in Step 2 of the Lu *et al.* (2007) FMCGDM model.

$$\mu_{\lambda}(x) = \begin{cases} 1 & \text{iff } x = \lambda \\ 0 & \text{iff } x \neq \lambda \end{cases} \quad [\text{Eqn 5}]$$

This binary property is used to define the left, middle and right points of the triangular fuzzy numbers that are taken from Lu *et al.* (2007). The associated fuzzy numbers (refer to Lu *et al.* 2007) represent each of the linguistic terms used in the pairwise comparison matrix E^n (which expresses the relative importance of the selection criteria) and the belief matrix B^n (which expresses the possibility of selecting a solution under a criterion) in Step 3 of the fuzzy decision support systems.

Results

To produce a priority ranking order for the ten outcome-based KPIs, based on their closeness to an ideal solution, intelligent FMCGDM models developed by Lu *et al.* (2007, 2008) were adopted. The process involved calculating the closeness coefficient for each decision alternative, thus:

$$CC_j = \frac{1}{2} \left(d_j + (1 - d_j^*) \right), j = 1, 2, \dots, m \quad [\text{Eqn 6}]$$

where d_j is the distance measurement between each element of the weighted normalised decision vector and the fuzzy negative-ideal solution, r^- (which is equal to 0) and d_j^* is the distance measurement between each element of the weighted normalised decision vector and the fuzzy positive-ideal solution, r^+ (which is equal to 1). Based on this modelling, the ranking for the outcome-based KPI alternatives for Revenue Management within Virgin Atlantic Cargo are shown in Table 3.

Based on these findings, it was observed that the outcome-based KPI *Network Optimisation* represents the most satisfactory solution. Other outcome-based KPIs of critical importance were *Optimising Density*, *Permanent Bookings (PB)/Free-sale Mix* and *Overbooking*. A closeness coefficient was observed for the KPIs *Flight Plan Audit*, *Dynamic Bid Price* and *Permanent Bookings Utilisation*, which all fell within an interval of 0.0101. It was considered that a more accurate determination of ranking for these outcome-based KPIs might be achieved through another round of multi-criteria group decision-making. It was then observed that the remaining three KPIs (*Empty Moves*, *Maintaining Station Budgets* and *Flight Plan Released*) were each much closer to the fuzzy negative-ideal solution than the others and may be considered as a low-priority for implementation. In

TABLE 3: Aggregated ranking of outcome-based key performance indicator alternatives.

Key performance indicator alternatives	Closeness coefficient
Network optimisation	0.57
Optimising density	0.52
Permanent bookings or free-sale mix	0.50
Overbooking	0.48
Flight plan audit	0.47
Dynamic bid price	0.47
Permanent bookings utilisation	0.46
Empty moves	0.36
Maintaining station budgets	0.32
Flight plan released	0.16

contrast, *Network Optimisation* and *Optimising Density* clearly represented the highest priorities for further development and implementation, on the basis that they had coefficients closer to r^+ than to r^- . This result confirms the general expectation arising from earlier specifications that these two outcome-based KPIs are particularly well grounded in air cargo Revenue Management theory. It also supports expectations that the measurement they can provide is supported by data that is of reasonably good data quality.

Conclusion

Revenue Management is a critical aspect of logistics and supply chain management practice (Ballou 2006). Within air cargo operations, Revenue Management is utilised to optimise overbooking in extremely competitive environments associated with growth and liberalisation of the airline industry.

Scholars, such as Blair and Anderson (2002) and Anderson and Blair (2004), view Revenue Management's role as critical within this context, mainly because the dynamic pricing of perishable goods with uncertain demand has become an important source of competitive advantage. It must, however, be pointed out that although studies (Ballou 2006; Amaruchkul Cooper & Gupta 2007) have been able to establish a direct, positive correlation between the application or utilisation of Revenue Management and increased firm profitability, gaining a clear understanding of critical decisional parameters of Revenue Management and how they impact on profit generation remains of key interest to air cargo operators. For example, operators may be interested in understanding not only which Revenue Management systems are associated with high operational performance, but also the extent to which it is possible to generalise across cargo operations and operational environments. This issue of generalisability is crucial. According to Anderson and Blair (2004:353), 'the continued success of Revenue Management hinges upon the ability to link organisational performance to the pricing and capacity decisions of Revenue Management systems'.

Within air cargo operations, the need to optimise Revenue Management is largely a matter of understanding the intricacies of the relationships between performance indices. The need for such understanding is driven by the fact that meaningful evaluation of key performance indices is not feasible without a clear quantification of their inter-relationships and trade-offs. The theoretical discussion has further emphasised the need to develop such understanding by exploring the unintended behavioural consequences of favoured indicators. Quantification enables clarity in terms of determining not only which indices dominate Revenue Management, but how such dominance ought to be sustained and replicated.

This study represents a major collaborative endeavour between industry and academia. In this study, outcome-based performance indicators were shown to play a considerable

role in Revenue Management. For example, such indicators provide the necessary quantitative benchmarking information that may be employed to effectively reduce 'spoilage' and overbooking; two major areas of focus in air cargo Revenue Management (Becker & Wald 2010; Moussawi-Haidar & Cakanyildirim 2012). This study focused on two primary aims, which were identified by the industry sponsors. The first was to establish the most valued outcome-based KPIs; the second was to identify the best approach towards the measurement of decisional performance (against established KPIs). Using a fuzzy group decision-making methodology, in line with earlier work by Malmi (2001), which emphasises that performance assessment may be more appropriately addressed by utilising a limited number of crucial indices, the authors generated a ranking order of ten outcome-based air cargo Revenue Management KPIs, which may serve as a platform for Virgin Air Cargo operators seeking to improve the reliability of the ranking order within Revenue Management.

Our suggested prioritisation of outcome-based KPIs should not, however, be regarded as a panacea. Inevitably brings with it possible problems that need to be addressed. A major challenge in performance measurement facing Virgin Air Cargo concerns just how reductionist performance measurement should be. For example, a more heavily reductionist approach based predominantly on outcome-based measures may appear attractive, as it generates a clear cognitive focus. Essentially, this allows for a more manageable theoretical endeavour, which explores only the relationships between what the core indicators measure. On the other hand, a key disadvantage of any such complexity reduction is that: it might neglect important unmeasured behavioural complexities and in overlooking such complexities, outcome-based KPIs generally fail to assess employee performance against strategic business areas such as customer service (Tung *et al.* 2011). Given that the need for KPIs to tap and cultivate long-term relationships has been increasingly recognised over the last twenty years (Ford & Hakansson 2010), we need to be wary of any possible organisational myopia caused by a narrow focus on outcome-based KPIs. Furthermore, there is an insubstantial amount of evidence to suggest that KPIs are consistently applied across the revenue-management chain. Hence it could be dangerous to impose theoretical generalisations when assessing KPIs across varying operational contexts. Echoing one of the core principles of the performance measurement revolution, Morgan (2007) suggested that to capture the realities of the operational environment, there must be a comprehensive appreciation among managers of the evolutionary nature of performance-management systems. It is further suggested that this comprehensive appreciation must extend into one that seeks to continually rebalance the advantages of generalisation against those of contextual specificity. Thinking at the behavioural impact level, managers must be able to create enough visibility of performance indices within the organisation to enable these indices to be properly understood as vehicles for not only operational effectiveness, but also transformation. The findings from this study are in

alignment with earlier studies by Morgan (2007). In effect, it is recommended that optimised operational decisions taken by air cargo revenue managers within Virgin Air Cargo may best be achieved through an emphasis on a limited number of widely understood outcome-based performance indices. These, however, are likely to best serve the operational objectives of Virgin Atlantic Cargo if vigilance concerning their behavioural effects is promoted across the organisation. This is likely to be more successful where employees are sensitive to the need to guard against both too much and too little rigidity in the organisation's use of KPIs.

This present study was limited in scope from the beginning. In the first place, the precise parameters of the study were controlled with the outcome-based KPIs under evaluation being stipulated by the industry sponsor (Virgin Atlantic Cargo). It was not our role to probe for behavioural or cultural issues relating to the use of these preferred indicators. This limitation, however, generates substantial opportunities for further studies that explore the use of KPIs such as the ones that were prioritised, giving thought to all the psychological and cultural issues that matter from the enlightened standpoint of the performance-measurement revolution. For example, future studies may seek to explore why preferred KPIs vary across the air cargo industry. Further studies might seek, in addition to the data collected from the Revenue Management team, to collect data from other operational units impacted by air cargo operations. In addition, further studies might also take on more of a design role, perhaps by developing KPIs from a literature base. This might provide a useful touchstone for assessing the KPI preferences of various cargo operators. Another key limitation with the study is that whilst the outcome-based indices that were advocated may emphasise revenue optimisation, behavioural-based indices tend to gather useful information on the *causes* of poor performance (Morgan 2007; Tung *et al.* 2011). Clearly, both types of measure may play important and mutually supportive roles in any organisation's performance-measurement system, and these mutual support roles deserve to be studied.

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Competing interests

The authors declare that they have no financial or personal relationship(s) which may have inappropriately influenced them in writing this article.

Authors' contributions

A.M. (University of Southampton), A.A. (Virgin Atlantic Cargo), U.O. (University of Johannesburg), Y.W. (University of Southampton), A.M. (University of Southampton) and M.C. (University of Southampton and University of Johannesburg) all made equal conceptual contributions that led to the development of this article.

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