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The Factors Affecting Airspace Capacity in Europe: A Cross-Sectional Time-Series Analysis Using Simulated Controller Workload Data

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Air traffic in Europe is increasing at a rapid rate and traffic patterns no longer display pronounced daily peaks but instead exhibit peak spreading. Airspace capacity planning can no longer be for the peak period but must consider the whole day. En route airspace capacity in the high density European air traffic network is determined by controller workload. Controller workload is primarily affected by the features of the air traffic and ATC sector. This paper considers the air traffic and ATC sector factors that affect controller workload throughout the whole day. A simulation study using the widely used Reorganized ATC Mathematical Simulator (RAMS) model of air traffic controller workload is conducted for the Central European Air Traffic Services (CEATS) Upper Area Control Centre region of Europe. A cross-sectional time series analysis of the simulation output is conducted with corrections for temporal autocorrelation in the data. The results indicate that a subset of traffic and sector variables and their parameter estimates can be used to predict controller workload in any sector of the CEATS region in any given hour.

KEY WORDS

1. Air Traffic Control. 2. Workload. 3. Capacity.

1. INTRODUCTION. The rapid rise in European air traffic has highlighted the role of ATC and controllers in the European aviation system. For example, in the period between 1985 and 1990, air traffic in Europe increased by 7·1% annually (EUROCONTROL, 1991). The forecast growth in air traffic for Europe between 1990 and 2010 is 110%, leading to over 11 million flights per year over Western Europe in 2010 (ATAG, 1992). In the United Kingdom alone, forecasts predict a growth rate of 4·25% in terminal passengers per year between 1998 and 2020 (The Department of Environment Transport Regions, 2000). This air traffic is not evenly distributed throughout Europe, with the existence of a core area consisting essentially of the London-Brussels-Frankfurt-Milan (including Paris) area where air

traffic density is highest. The consequence of predicted traffic growth is that controllers, already very busy in the core area, will have to control more aircraft.

A major impact of this air traffic growth has been a rise in flight delays in Europe. For example, the increase in air traffic, and hence the work required by controllers to safely control it, was a major contributor to flight delays in the second half of the 1980s. Over a period of four years, the number of flights in Europe delayed by at least 15 minutes has almost doubled (ECAC, 1998). The economic impact of delays, as well as other inefficiencies in the ATC system (e.g. non-optimal flight profiles), was calculated to cost Europe US \$5[1] billion (Lange, 1989). The main cause of these inefficiencies has been the lack of a single, integrated ATC system throughout Europe. With nations zealously guarding the sovereignty of their airspace, the practice has been for each nation to manufacture, own and control the ATC infrastructure and manage the air traffic within their airspace, leading to technology incompatibilities and duplication of tasks and information. The European Commission has planned to reform the European air traffic control system with the aim of creating a "single European sky" (European Commission, 2001). Such a move should lead to a consolidation of air traffic management providers, and eventually reduce the number of centres controlling flights across Europe from the current 49 to perhaps four or five. The regulatory framework is expected to be in place for the Single European Sky by the end of 2004 (European Commission, 2003; The Financial Times, 2003).

Since the late 1980s there have been various efforts led by the European Organisation for the Safety of Air Navigation (EUROCONTROL)[2], to develop initiatives to tackle en route airspace capacity problems (ECAC, 1990). Initially there was the European Air Traffic Control Harmonisation and Integration Programme (EATCHIP) (EUROCONTROL, 1991) which tried to progressively harmonize and integrate the diverse ATC systems throughout Europe. To cope with the predicted air traffic demands, the current European Air Traffic Management Programme (EATMP) envisages a gate-to-gate concept, in which flights are treated as a continuum, from the first interaction with ATM until post-flight activities (EUROCONTROL, 1998). To achieve this, a broad range of procedures and technologies are considered which have the potential to change the way in which controllers work in the future.

Within the European air transport network, the primary constraint at the busiest airports, e.g. London Heathrow, is the lack of runway capacity. However, for airports that are not runway constrained, the en route airspace capacity provides a major constraint. Within the gate-to-gate concept of EATMP, initiatives to increase current enroute airspace capacity, as well as those considering future capacity scenarios, need a reliable definition and measure of airspace capacity. The problem here is that in the dense European air traffic environment, en route airspace capacity depends not only upon spatial-geometrical separation criteria, but also on the workload of air traffic controllers (Arthur D. Little, 2000). There is then a need to understand controller workload and the factors that drive it. This paper attempts to better analyse en route airspace capacity, which is a major component of gate-to-gate capacity.

[1] This figure is in 1988 US \$.
[2] EUROCONTROL is the pan-European organisation established in 1960 to co-ordinate European air traffic control and air traffic management (ATC/ATM).

Another emerging problem in European airspace capacity estimation is that air traffic patterns no longer display pronounced daily peaks. Rather, there appears to be a peak spreading throughout the day making planning approaches based on daily peaks inappropriate. Instead, to improve airspace capacity planning, it is important to understand the factors that affect controller workload, and their impact throughout the day.

This paper provides a method to assess the impact of these factors on controller workload throughout the day, known as cross-sectional time series analysis. This analysis should help to develop a reliable functional relationship between air traffic controller workload and the various factors that affect it. The research presented in this paper uses a realistic simulation model of air traffic controller's workload to do this. Section 2 of the paper provides a brief explanation of the European airspace capacity estimation problem, emphasising the critical role of the air traffic controller workload. Section 3 examines the factors that affect controller workload and airspace capacity. Section 4 discusses the issues to be considered in a simulation exercise involving air traffic controller workload, whilst Section 5 outlines the Reorganized ATC Mathematical Simulator (RAMS) (EUROCONTROL; 1996a, 1996b) to be used in a series of simulation experiments. Section 6 outlines the main features of the simulations. The methodology of cross-sectional time series analysis, also known as panel data analysis, is discussed in Section 7. Section 8 then shows the results of a panel data analysis, based on regression for a simulation scenario over a 20-hour period. Section 9 develops the panel data model to account for temporal autocorrelation. Section 10 investigates the predictive abilities of the model when compared to both the actual workload for a sector obtained after a simulation and its pattern throughout a 20-hour period. The paper is concluded in Section 11.

2. EUROPEAN AIRSPACE CAPACITY ESTIMATION.

Experience in Europe suggests that en route airspace capacity e.g. that of an ATC sector, is determined by air traffic controller workload i.e. the mental and physical work done by the controller to control traffic (Majumdar and Polak, 2001). This is in addition to spatial-geometric and temporal criteria based upon the performance characteristics of the aircraft in the sector (EUROCONTROL, 1991).

The capacity of an ATC sector can therefore be defined as the *maximum number of aircraft that are controlled in a particular ATC sector in a specified period*, while still permitting an *acceptable level of controller workload*. Note that this is a volumetric (or density) capacity measure, i.e. aircraft in a sector whose control generates work for the controllers, rather than a flow measure i.e. the number of aircraft entering, exiting the sector, in a given period of time. Such a definition requires three criteria to be determined:

- the definition of controller workload;
- a method for measuring controller workload; and
- quantification of an acceptable level of controller workload, i.e. the threshold value at full capacity.

Controller workload is a confusing term and with a multitude of definitions and models in the literature. Its measurement is not uniform (Jorna, 1991). It is important to note that workload is a construct, i.e. a process or experience that cannot be seen directly, but must be inferred from what can be seen or measured. Research, theory, models and definitions of workload are interrelated and there are numerous reviews of workload and its measurement (e.g. Gawron et al., 1989; Hopkin, 1995).

The practice in en route airspace capacity estimation in Europe is to use simulation modelling of controller workload where the workload is given by task-time definitions obtained from a detailed non-intrusive objective record of the controller's actions by an independent observer (EUROCONTROL, 1996a). Apart from the expense associated with obtaining such a record, there is a problem in accounting for the non-observable mental tasks of a controller, e.g. planning. Therefore, there is a need for such records to be supported by controller verification of the tasks and their timings, especially for those tasks that involve a significant mental component. Based upon these task-time definitions, threshold controller loadings are defined for the number of minutes/hour that controllers are occupied in their tasks as recorded by the models, e.g. RAMS and DORATASK, described in more detail in Section 5. (EUROCONTROL 1999a; Stamp, 1992). En route airspace capacity, e.g. of an ATC sector, is then defined as the maximum number of aircraft controlled in a sector per hour given this threshold controller loading.

3. AIRSPACE CAPACITY DRIVERS. It has already been stated that en route airspace capacity is primarily determined by controller workload. Research indicates that the workload experienced by air traffic controllers, however it is defined and measured, is affected by the complex interaction of (Mogford et al., 1995):

- the situation in the airspace – i.e. by features of both the air traffic and the sector;
- the state of the equipment – i.e. by the design, reliability and accuracy of equipment in the control room and in the aircraft; and
- the state of the controller, e.g. the controller's age, experience, decision-making strategies.

These parameters can be thought of as the drivers of controller workload, and consequently of en route airspace capacity, i.e. *airspace capacity drivers*. Thus the effect of these parameters on controller workload must be understood if realistic and successful strategies for increasing airspace capacity are to be implemented.

Figure 1, based on Mogford et al., 1995, outlines how these capacity drivers affect controller workload. Mogford et al., 1995 state that the situation in the airspace is the primary factor affecting workload and is determined by:

- physical aspects of the sector, e.g. size or airway configuration; and
- factors relating to the movement of air traffic through the airspace, e.g. the number of climbing and descending flights; and
- a combination of the above factors which cover both sector and traffic issues, e.g. required procedures and functions.

This interaction between sector and traffic features can be thought of as ATC complexity, and it is this that generates workload for the controller.

There are various reviews of the effect of these drivers on controller workload (Mogford et al., 1995; Majumdar and Ochieng, 2002). From these sources a list of factors that impact upon controller workload can be derived (Table 1). There have

Table 1. List of air traffic and sector factors that can affect ATC complexity and controller workload.

Air Traffic Factors	Sector Factors
Total number of aircraft	Sector size
Peak hourly count	Sector shape
Traffic mix	Boundary location
Climbing/descending aircraft	Number of flight levels
Aircraft speeds	Number of facilities
Horizontal separation standards	Number of entry and exit points
Vertical separation standards	Airway configuration
Minimum distance between aircraft	Proportion of unidirectional routes
Aircraft flight direction	Number of facilities.
Predicted closest conflict distance	Winds
Flow entropy	
Number and type of conflicts	
Aircraft Clustering	
Amount of time aircraft is controlled	
Changes in altitude/heading/speed	

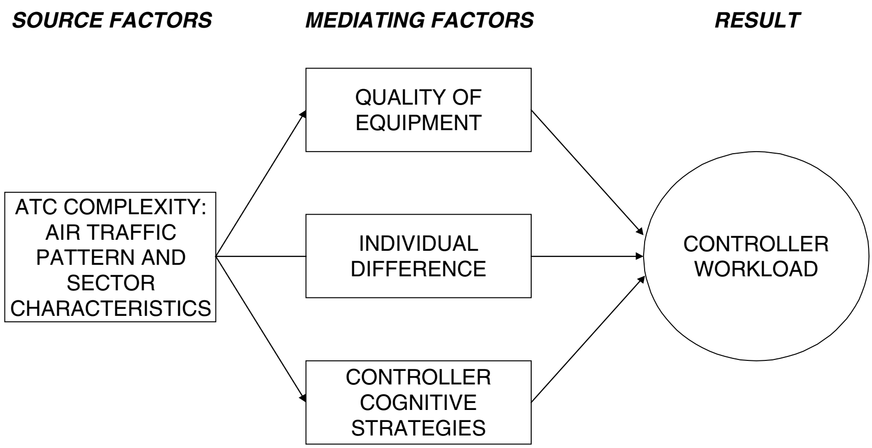

Figure 1. Factors affecting controller workload.

been various recent attempts to quantify the effect of ATC complexity on controller workload, using either:

- real-time simulations (i.e. mock up facilities) followed by controller questionnaires, e.g. the dynamic density concept of NASA (Laudeman et al., 1998; Sirdhar et al., 1998); or
- the analysis of historic data e.g. by the FAA human factors group (Rodgers et al., 1998) on the separation loss between aircraft, from the Atlanta airspace sectors.

Recent research in Europe on air traffic complexity indicators by Granger and Durand, 2003, and by Christien and Benkouar, 2003, has reinforced previous findings, whilst adding new factors that can affect controller workload, e.g. flow entropy. The research undertaken by Mills et al., 2002 and Manning et al., 2003 using

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empirical data from en route control centres in the USA, has further confirmed many of the factors listed in Table 1. Another approach used by Majumdar and Polak, 2001 and Majumdar and Ochieng, 2002 specifically for European airspace, used simulation to model airspace and controller workload. The output of the simulation was used to formulate a functional relationship between airspace capacity, given a threshold value for controller workload, and the relevant drivers.

An important point arises from the research on the effect of airspace capacity, namely that more than just a single air traffic variable affects workload and, given a threshold workload value, airspace capacity. Therefore estimating airspace capacity based upon the relationship between controller workload and single air traffic variable, i.e. the number of aircraft entering the sector in given period (outlined in EUROCONTROL, 1996a), is not totally adequate.

Both the previous studies by Majumdar and Polak, 2001, and Majumdar and Ochieng, 2002 considered just the peak workload hour of the simulation. This current research goes further by considering the drivers that affect controller workload in a region of European airspace throughout the day. This should help ATC/ATM planners and managers in their task by enabling them to estimate accurately the controller workload throughout the day based upon a particular set of drivers in any given sector at any given time of day. The following section describes this simulation modelling approach in more detail.

4. SIMULATION MODELLING OF EUROPEAN EN ROUTE AIRSPACE.

Wickens et al., 1997 state that simulation models are often necessary in ATC because of the system's great complexity. In addition, the inherently dynamic behaviour of the airspace is well suited for a dynamic simulation. Magill 1997, 1998 also notes the advantages of simulation modelling in ATC capacity estimation. Simulation allows a careful definition of the rules for its elements in order to investigate their interaction and on completion of the simulation, analyze the output to derive functional relationships at an aggregate level. However, three questions need to be answered in order to make effective use of simulation modelling:

- How will the work done by the ATC system be characterised by the simulation model?
- How well does the simulation model used represent the reality of the ATC system?
- What rules for the elements of the simulation model need to be encompassed for the simulation scenarios in order to generate the appropriate output for analysis?

The task time thresholds mentioned in Section 2 for various air traffic controller workload simulation models deals with the first of these questions. These thresholds have been validated by several real-time studies and the experience gained from previous simulation results, as well as from field studies (Stamp, 1992; EUROCONTROL 1999a, 1999b, 1999c).

As a priority, it is important to ensure that the simulation model chosen realistically reflects the real world airspace environment under consideration. Furthermore, it should be calibrated to give reasonable estimates of workload. The following section outlines the features of the simulation model used this study.

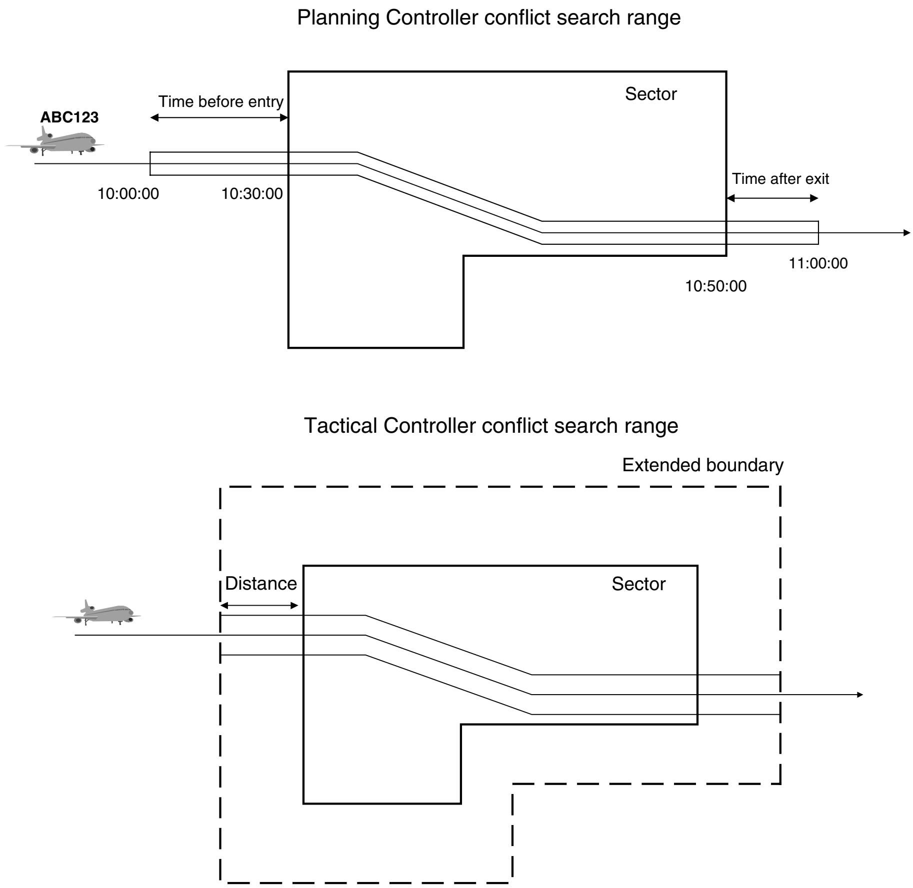

Figure 2. The control elements in RAMS.

5. THE REORGANIZED ATC MATHEMATICAL SIMULATOR (RAMS). There are two major simulation controller workload models, DORATASK (Stamp, 1992) – developed and used specifically for the UK's ATC sectors, where its results have been validated – and the Reorganized ATC Mathematical Simulator (RAMS) (EUROCONTROL, 1995). In addition, a model of air traffic controller workload based upon the cognitive tasks of a controller has been developed by NATS, known as the Performance and Usability Modelling in ATM (PUMA) Model (Kilner et al., 1998) and is used for analysing data from real time simulations, i.e. trials using controllers in mock-up control rooms.

The RAMS model chosen for the research presented in this paper, is a discrete-event simulation model which, together with its predecessor the European Airspace Model, has been used widely for 25 years in Europe for airspace planning. The model has been verified by controllers (EUROCONTROL, 1999a). In the model, each control area is associated to a sector, which is a 3-dimensional volume of airspace as defined in the real situation. Each sector has two control elements (planning and tactical) associated with it (see Figure 2). The control areas maintain information regarding the flights wishing to penetrate them, and have associated separation

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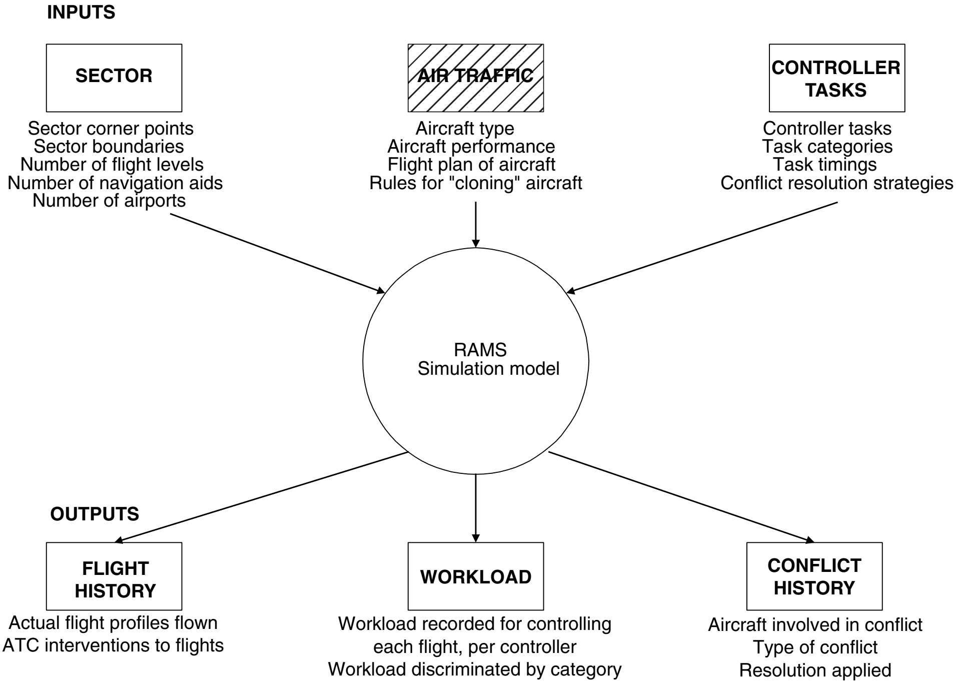

Figure 3. The inputs and outputs into the RAMS model.

minima and conflict resolution rules that need to be applied for each of the two RAMS control elements. This reflects the teamwork aspect of control seen in practice. Also, the simulation engine permits the input of rules for these controllers that mimics reality. The task base in RAMS contains a total of 109 tasks undertaken by controllers, together with their timings and position, grouped into five major areas. These tasks are derived from a number of reference sectors in Europe, which include sectors in the London region, Benelux countries, France and Germany. Furthermore, a cloning engine enables the current air traffic to be cloned to produce future traffic demands. The use of RAMS for this study means that the EUROCONTROL definition of a control team (Tactical and Planning) at capacity of 42 minutes/hour loading, has been adopted.

It is important to point out that a range of methodological issues has to be addressed to ensure the veracity of the results of a simulation model. In particular, it must be ensured that the simulation replicates the real world situation as closely as possible. Figure 3 shows the major inputs and outputs of the RAMS model. The application of appropriate "rules" for the inputs to RAMS, deals with the following issues of the simulation:

- The area of airspace simulated represented by the characteristics of the ATC sectors and the air routes through them as contained in the sector data input files.
- The air traffic simulated represented by the characteristics of the aircraft and their performance capabilities as contained in the air traffic data input files;

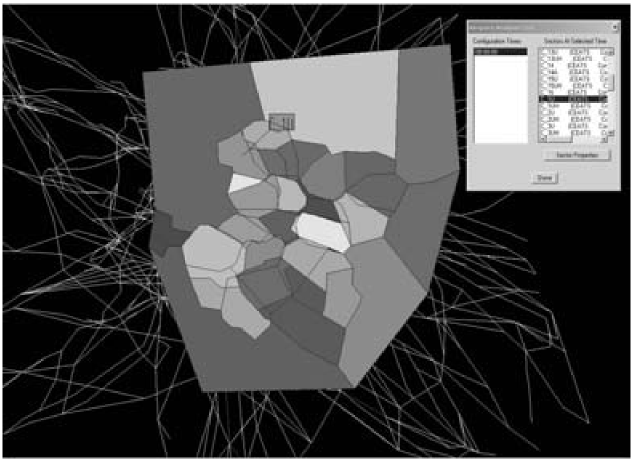

Figure 4. The CEATS Simulation Area.

- The simulated controller tasks represented by the set of controller tasks and their timings as contained in the controller task input files. The choice of an appropriate set and its implications are of the utmost importance in both undertaking and understanding the simulation results.

The following section considers the simulation inputs to RAMS used in this research taking into account the methodological issues above.

6. THE SIMULATION SCENARIO. The simulation study was conducted for the Central European Air Traffic Services (CEATS) Upper Area Control Centre, comprising the en route airspace of Austria, Bosnia and Herzegovina, Croatia, Czech Republic, Hungary, Italy, Slovak Republic and Slovenia. The airspace of the CEATS region consists of 46 contiguous sectors with thirteen Area Control Centres (ACCs) as shown in Figure 4. This gives a sufficiently large number of heterogeneous ATS sectors for subsequent analysis.

The traffic sample used consisted of 5400 flights in twenty hours, following a standard route structure. The flight data is contained in traffic profiles of the scheduled flight data for a particular day. Individual flights are defined by an entry time, entry cruise and exit levels, aircraft model, flight plan of navaids, airports and runways (i.e. the route of the flight). Flight profiles are dictated by the flight plan and aircraft performance. The flight path is 4-dimensional, containing 3-dimensional positions in space, each associated with time of arrival. The aircraft performance is dictated by each flight's aircraft model. The aircraft model is defined by two attributes, the;

- performance group i.e. climb and descent speeds and rates and
- aircraft group, which is used to specify wake turbulence separations.

Only the climb and descent rates to reach the requested flight levels are varied. The cruise, climb and descent speeds represent ground speed and are not varied. As a consequence, overtaking conflicts between aircraft on the same route and same flight level were not modelled. Whilst the implications of this are difficult to speculate, it

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Table 2. Controller rules input data in the simulations.

Attribute	Planning Controller	Tactical Controller
Planning Controller Window entry/exit distance before/after sector (mins)	15 minutes	Not applicable
Radar Window entry/exit distance before/after sector (nm)	Not applicable	20
Radar Window entry/exit distance above/below sector (100's ft.)	Not applicable	20
Vertical Separation	ICAO Separation Rules 1000 feet below FL290 2000 feet above FL290	ICAO Separation Rules 1000 feet below FL290 2000 feet above FL290
Lateral Separation (nm)	10·0	10·0
Longitudinal Separation (nm)	10·0	10·0
Detection Dynamics	Defined Detection Dynamics	Defined Detection Dynamics.
Controller Task Base	CEATS Tasks.	CEATS Tasks
Controller Rule Group	Planning Rules	Tactical Rules
Entry Distribution	RAMS Default Distribution	RAMS Default Distribution*
Conflict Detection model	Rectangle	Rectangle
Sector Clipping	60 seconds	60 seconds

* This applies to the handoff entry time to the tactical controller.

may be that the use of the other resolution strategies, e.g. those where the trailing aircraft slows down, compensates adequately for realism in the simulations.

Table 2 lists the main air traffic controller input rules used for the simulation study. The controller tasks and their timings used in this analysis take into account the technology and procedures used in the CEATS area and were verified by air traffic controllers of this area. It includes tasks in the five main areas of controller activity accounted for in the RAMS model:

- Co-ordination tasks consisting of external communications with other ATC units and internal coordination within the simulated ATC unit.
- Flight data management tasks.
- Planning conflict search tasks to determine ATC clearances.
- Routine Radio/Telephone communications.
- Radar Tasks consisting of radar handovers and co ordinations, radar supervisions, radar interventions and vectoring.

This task base adequately captures the major components of the air traffic controller's tasks. Conflict detection and resolution are major elements of the controller's tasks and there is a need to adequately model these aspects. The following parameters were used for conflict detection between aircraft, based upon the experience of the controllers in the CEATS region:

- Vertical separation – conventional vertical separation minima (CVSM) of 2000 feet above Flight Level (FL) 290, i.e. 29 000 feet, and 1000 feet below FL 290.
- Horizontal separation – lateral and longitudinal separation of 10 nautical miles between aircraft.

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These horizontal and vertical separation parameters create a rectangular conflict zone around the flight, rather like a tunnel when projected through time. By the use of dynamic separation multipliers the separation between aircraft can be increased based upon the relative positions between the two flights. These multipliers rely on the dynamic situation of the flights during the simulation, and not on the static values defined by airspace and aircraft type. The multipliers provide increased realism into the conflict detection and the values chosen reflect the much greater separation that must be required, for example, between aircraft approaching each other than when aircraft are parallel to each other. They are derived from consultations with ATC personnel involved in the RAMS simulation for the CEATS area.

7. PANEL DATA METHODOLOGY. The output data from RAMS of interest in this analysis are those for the workload and the flight history (Figure 3). Thus, for a given traffic demand pattern in the CEATS area, an attempt is made to fit an analytical model to the RAMS output data to formulate a relationship between controller workload and the variables that affect it (i.e. various flight and sector data, throughout the day). The need is therefore to consider the factors affecting controller workload not just in the peak hour, but also in successive time periods, as well as account for the heterogeneous nature of the sectors in the CEATS region.

A technique used in econometrics that accounts for both heterogeneity and time is the cross-sectional time-series, or "panel data" analysis (Baltagi, 1995). Panel data in econometrics traditionally refers to the pooling of observations on a cross-section of households, countries, firms etc., over several time periods. This can be achieved by surveying a number of households or individuals and following them over time. In the case of airspace capacity analysis, panel data refers to the pooling of observations on a cross-section of ATC sectors over several periods of time, e.g. one hour intervals. The major benefits of using panel data are (Baltagi 1995):

- Controlling for individual heterogeneity. Panel data analysis assumes that individuals, countries and in the case of airspace research, ATC sectors, are heterogeneous. Time-series and cross-section studies, which do not control for this heterogeneity, run the risk of obtaining biased results.
- Provision of more informative data, more variability, less co-linearity among the variables, more degrees of freedom and more efficiency. Time-series studies suffer considerably from high co-linearity in the data. This is less likely with a panel across ATC sectors since the cross-section dimension adds a lot of variability, adding more informative data. With more informative data, reliable parameter estimates can be produced.
- The data are better suited to study the dynamics of adjustment. Cross-sectional distributions that look relatively stable hide a multitude of changes. Only panel data can relate the experience and behaviour of an individual sector at one point in time to other experiences and behaviour at another point in time.
- The data are better suited to the identification and measurement of effects that are simply not detectable in pure cross-sections or pure time-series data.
- The data models allow constructing and testing more complicated behavioural models than purely cross-section or time-series data.

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Table 3. List of independent variables obtained from the RAMS output.

Air Traffic Factors	Airspace geometry Factors
Total number of aircraft	Sector shape
Number of aircraft in continuous cruise profile	Number of flight levels available
Number of aircraft in cruise-descend profile	Number of navaids
Number of aircraft in cruise-climb profile	Number of airports
Number of aircraft in climb-climb profile	Number of neighbouring sectors from which aircraft enter
Number of aircraft in descend-climb profile	
Number of aircraft in descend-descend profile	Number of neighbouring sectors sectors to which aircraft exit
Number of aircraft entering sector in cruise	
Number of aircraft entering sector in climb	
Number of aircraft entering sector in descent	
Number of aircraft exiting sector in cruise	
Number of aircraft exiting sector in climb	
Number of aircraft exiting sector in descent	
Average flight duration in sector	
Total flight time in sector	
Aircraft speeds	

- The data are usually gathered on micro units, such as individuals, or in the case of capacity analysis, ATC sectors. Many variables can be more accurately measured at a micro level, and biases resulting from aggregation over firms or individuals are eliminated.

Based upon the above, a panel data (i.e. cross-sectional time-series) analysis on the basis of the output of the RAMS CEATS simulation seems an appropriate method for estimating the functional relationship between controller workload and its drivers (i.e. a number of possible independent variables, outlined in Table 3).

This RAMS simulation output data can be analyzed using a fixed effects time-series cross-sectional model. The data is at the sector-level and the inclusion of fixed effects allows for the control of other factors that might have influenced controller workload for which data is unobservable (Verbeek, 2001). For example, this could include specific ATC procedures that may have been implemented in some ATC sectors. These methods are simple to implement and consist of ordinary least squares (OLS) regression with a dummy variable included for each cross-section, in this case the sector. The OLS estimators have optimal properties when the Gauss-Markov conditions are met. This means that the estimators are unbiased, linear and have the minimum variance of any class of linear, unbiased estimators, i.e. they are "best". For the standard fixed effects model:

$$y_{it} = \alpha_i + x'_{it}\beta + \varepsilon_{it} \tag{1}$$

the error term ε_{it} is assumed to be independent and identically distributed over individuals i (i.e. the ATC sectors) and time, with zero mean and variance σ^2_ε (Verbeek, 2001). The workload in sector i in time t is y_{it} and β represents the coefficients. x_{it} is a K-dimensional vector of explanatory variables, not including a constant. This means that the effects of change in x are the same for all units and all periods, but that the average level for unit i may be different from that unit j. α_i thus

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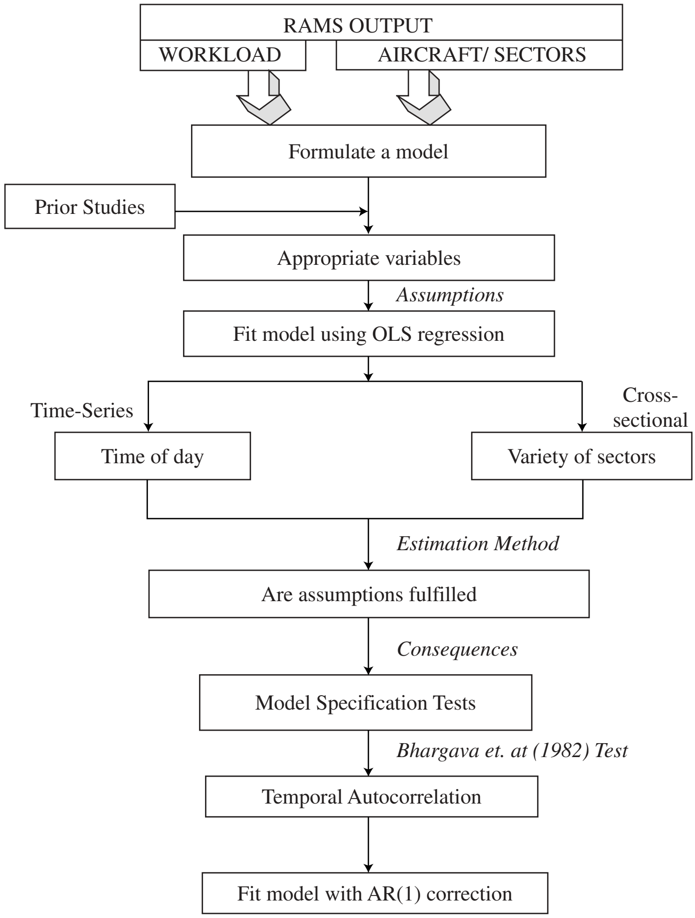

Figure 5. The modelling strategy for cross-sectional time-series analysis.

captures the effects of those variables that are peculiar to the *i*-th individual and that are constant over time. α_i are treated as N fixed unknown parameters. After fitting a model, there is then a need for diagnostic testing to ensure the appropriate model has been selected.

An alternative approach to the fixed-effects panel data model is the random effects panel data approach (Verbeek, 2001) which views the individuals in the sample as a random draw from some underlying population. However, given that the individuals in the sample are very similar, i.e. sectors in the CEATS region, they cannot be viewed as a random draw and the fixed effects approach is appropriate. The strategy used to attempt to formulate a functional relationship between controller workload and appropriate air traffic and sector variables is outlined in Figure 5.

8. PANEL DATA ANALYSIS.

The data based upon the CEATS area simulation considers a 20-hour day for each of the 46 sectors. This data is analyzed using a fixed effects time-series cross-sectional model. Therefore, repeating equation (1)

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for the standard fixed effects model:

$$y_{it} = \alpha_i + x'_{it}\beta + \varepsilon_{it} \qquad (2)$$

where the dependent variable, y_{it} is the workload of the combined air traffic control team of planning and tactical controller in the hour, measured in seconds. The independent variables, x_{it}, chosen for the panel data analysis are:

- The different types of flight profile through the sector.
- The different phases of flight when entering a sector.
- The different phases of flight when exiting a sector.
- The total flight time of all flights through the sector.
- The average flight time through the sector.
- Two independent variables relating to the number of surrounding sectors from which flights enter and exit a sector.
- A variable for the difference in speed between the fastest and slowest aircraft in the sector.
- A variable for the difference in the highest and lowest flight levels used in the sector.

A time trend variable is also included in the analysis to control for variation over time due to unobserved factors. The results of the panel data analysis are shown in Table 4.

The parameter estimate for a significant variable x (as obtained by the t-test for the variable having a value >2 at the 5% significance level) indicates that the effects of change in x are the same for all units and all periods. Based upon this the major findings from this panel data analysis are as follows.

Whilst it is surprising that the variable, number of aircraft in continuous cruise profile is not statistically significant at the 5% level of significance, three flight profile variables are significant:

- The number of aircraft with cruise-climb profile. Each aircraft with a cruise-climb increases controller workload by 37 seconds.
- The number of aircraft with cruise-descend profile. Each aircraft with cruise-descend profile increases controller workload by 12·5 seconds.
- The number of aircraft with climb-climb profiles. Each aircraft with a climb-climb profile increases controller workload by 49 seconds.

With respect to flight times in the sector, the average time spent in the sector was found not to be significant, whilst the total flight time was found to be significant at the 5% level. Every second of the total flight time variable increases controller workload by 0·012 seconds.

The variable for the difference in flight levels used is significant and negative, indicating that for every difference of one flight level, controller workload decreases by one second. This implies that the more flight levels there are in a sector, the less the workload associated with factors such as conflict resolution. Presumably more flight levels give controllers more options to avoid conflicts in a sector.

The speed difference variable is significant and indicates that for every 1 kt speed difference between the fastest and slowest aircraft in the sector, controller workload increases by 0·32 seconds. Therefore, the greater the speed homogeneity in a sector, the more preferable it is for controller workload, i.e. less workload.

Table 4. Results of the fixed effects cross-sectional time series analysis for the CEATS Region.

Dependent variable = Total workload in hour			
	Hour 2–Hour 22		
Hours of data	Coefficient	Std Error (SE)	t-statistic
Time	−3·46	1·09	−3·16
Number of aircraft in continuous cruise profile	−0·01	4·53	−0·00
Number of aircraft in cruise-climb profile	37·43	5·07	5·07
Number of aircraft in cruise-descend profile	12·52	5·68	2·20
Number of aircraft in descend-descend profile	−4·35	6·82	−0·64
Number of aircraft in descend-climb profile	17·33	11·54	1·50
Number of aircraft in climb-climb profile	49·37	8·30	5·94
Total flight time	0·012	0·004	3·13
Average flight time	0·053	0·04	1·30
Flight level difference	−1·05	0·21	−5·09
Speed difference	0·32	0·32	3·34
Number of neighbouring sectors flight entry	−12·87	5·71	−2·26
Number of neighbouring sectors flight exit	−13·26	5·45	−2·43
Number of flights entering in cruise	35·12	3·47	10·11
Number of flights entering in climb	12·98	4·19	3·10
Number of flights entering in descent	61·92	4·37	14·17
Number of flights exiting in cruise	7·94	2·79	2·85
Number of flights exiting in climb	0·11	7·15	0·01
Number of flights exiting in descent	9·23	4·25	2·17
N	919		
R-Squared	0·91		
Rho_ar	0·58		

The shaded rows indicate significant variables at the 5% level.

The variables for the number of neighbouring sectors from which aircraft enter a sector, and exit from a sector were found to be significant and negative. Therefore, for every neighbouring sector into which aircraft could enter or from which they could exit, controller workload decreased by 12 to 13 seconds. A possible explanation for this is that whilst more sectors indicate increased coordination workload, this effect is counteracted by the reduced workload for conflict detection and resolution in any sector, though sector size effects need to be considered in this case. In addition, the neighbouring sectors could indicate spatial effects in the data not adequately captured by the variables present in this analysis.

Barring the number of aircraft exiting a sector in climb, all the other variables relating to flight phases for aircraft entry and exit into a sector are significant and positive in sign and value. This indicates that these variables combining both sector entry/exit and flight phase increase controller workload, the actual amount varying between 61 seconds for flights entering sector in descent and 9 seconds for flights exiting sector in descent.

The time trend variable is significant and negative. This indicates that some other factor not controlled for is also influencing controller workload in a negative way over time. This could be due for example, to procedures that aim to reduce controller workload throughout the day, or may represent some serial correlation in the data that is explored in greater detail in the following section.

It is worth noting that these results regarding the significance and interpretation of the variables is only valid for the CEATS simulation, i.e. tasks, traffic and sector patterns in the CEATS area, although the methodology developed should be transferable.

9. PANEL DATA TEMPORAL AUTOCORRELATION.

After fitting a model, there is a need to examine the error estimates obtained in order to confirm that their distribution is in accord with preconception (Upton and Fingleton, 1985). The presence of auto correlated errors in the data leads to a deviation from the Gauss-Markov conditions required for ordinary least squares (OLS) estimation. In this case for the error covariance matrix V, the off-diagonal cells of V contain non-zero values, which violates the conditions of the OLS procedure. Thus, although the OLS estimator is unbiased and linear, it does not have minimum variance, i.e. is not "best".

Such serial autocorrelation, defined as the correlation between members of a series of observations, can occur in either time-series or spatial data. It is easier to deal with such autocorrelation in time series since such observations are ordered in chronological order and there are likely to be interrelations among successive observations, especially if the time between successive observations is short. Should such autocorrelation exist, then the distribution of the ε_{it} will have the same form as that of the estimated $\hat{\varepsilon}_{it}$, but, whilst having the same zero mean, it will have a modified variance-covariance structure. Therefore, if the model selected has the correct form, the probable distribution of ε_{it} can be assessed by studying the distribution of the $\hat{\varepsilon}_{it}$. If $\hat{\varepsilon}_{it}$ has independent observations from a normal distribution, then it is probable that this was true for ε_{it}. If they are autocorrelated, then it is probable that the ε_{it} were also autocorrelated. Of course, if the models chosen are inappropriate, then the estimated "errors" will include a mixture of experimental error and model error, in which case it is difficult to make any useful deductions concerning the error distribution.

Spatial autocorrelation may well exist in this data given that the units of observation are the sectors of the CEATS area, and that the pattern of workload in the different regions of the CEATS region, e.g. the north or the south, is likely to differ from one geographical region to another, although substantially similar within a given region. Consider for this study just the potential temporal autocorrelation (or serial correlation) in the data. When serial correlation follows a first-order autoregressive (AR) process the error term is assumed to depend upon its predecessor as,

$$\varepsilon_{it} = \rho\varepsilon_{i,\,t-1} + v_{it} \tag{3}$$

where $|\rho| < 1$, and v_{it} is i.i.d. $(0, \sigma_v^2)$ across individual sectors and time. Typically the autocorrelation coefficient ρ and σ_v^2 are unknown. Testing the null hypothesis of $H_0{:}\rho = 0$, i.e. no autocorrelation, against the one-sided alternative $\rho < 0$ or $\rho > 0$, in a first order autoregressive process has a long history of producing test statistics with extremely complicated distributions. This tradition has continued with extensions of these tests to cross-sectional time series data. Bhargava et al., 1982 proposed the extension of the Durbin-Watson statistic to the case of balanced equally spaced panel datasets. If $\hat{\varepsilon}_{it}$ denotes the residuals, then Bhargava et al., 1982 suggest the following

Table 5. Results of the fixed effects cross-sectional time series with an AR(1) error analysis for the CAETS Region.

Dependent variable = Total workload in hour			
	Hour 3–Hour 22		
Hours of data	Coefficient	SE	t-statistic
Number of aircraft in continuous cruise profile	2·47	4·54	0·24
Number of aircraft in cruise-climb profile	32·90	5·40	6·09
Number of aircraft in cruise-descend profile	13·02	5·60	2·32
Number of aircraft in descend-descend profile	−5·00	7·29	−0·69
Number of aircraft in descend-climb profile	13·25	11·35	1·17
Number of aircraft in climb-climb profile	36·66	8·66	4·23
Total flight time	0·012	0·004	3·07
Average flight time	0·05	0·041	1·16
Flight level difference	−0·81	0·22	−3·64
Speed difference	0·25	0·09	2·77
Number of neighbouring sectors flight entry	−10·75	5·69	−1·9
Number of neighbouring sectors flight exit	−7·47	5·43	−1·37
Number of flights entering in cruise	37·14	3·27	11·35
Number of flights entering in climb	24·36	4·91	4·96
Number of flights entering in descent	67·41	4·97	13·57
Number of flights exiting in cruise	3·75	2·79	1·34
Number of flights exiting in climb	0·87	6·89	0·13
Number of flights exiting in descent	3·31	4·20	0·79
N	873		
R-Squared	0·882		DW = 1·50
Rho_ar	0·28		B-W = 1·57

The shaded rows indicate significant variables at the 5% level.

generalization of the Durbin-Watson statistic:

$$dw_p = \frac{\sum_{i=1}^{N} \sum_{t=2}^{T} (\hat{\varepsilon}_{it} - \hat{\varepsilon}_{i,t-1})^2}{\sum_{i=1}^{N} \sum_{t=1}^{T} \hat{\varepsilon}_{it}^{\,2}} \tag{4}$$

This allows for autocorrelation over time with the restriction that each individual has the same autocorrelation coefficient ρ. Using similar derivations as Durbin and Watson, Bhargava et al., 1982 were able to deliver lower and upper bounds on the true critical values that depend upon N, T and K (i.e. a K-dimensional vector of explanatory variables, not including a constant) only. Bhargava et al., 1982 suggest that for panels with very large N, if the computed statistic dw_p is less than two, then there is positive autocorrelation.

Results for the estimation of a model fitted with an AR(1) model to the disturbance term are shown in Table 5. It is evident that there is a high degree of temporal autocorrelation in the data, with the ρ values for the linear model being 0·28. The residuals $\hat{\varepsilon}_{it}$ from this model provide a test statistic for the Bhargava et al., 1982 modified Durbin-Watson statistic of 1·50, clearly indicating serial correlation in the data.

Comparing the results for a model with an AR(1) error term, with those obtained without accounting for serial correlation, gives the following major findings:

- Whilst the same flight profile variables are still significant, the parameter values have changed somewhat. Primarily, the parameter value for the number of

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aircraft in climb-climb profile changes considerably reducing from 49·37 seconds in the model with no serial autocorrelation to 36·66 for the model where serial autocorrelation is accounted for. The parameter estimate for the variable of the number of aircraft in cruise-descend profile remains the same for both models, whilst that for the number of aircraft in continuous cruise profile reduces slightly from 37·43 seconds to 32·90 seconds.

- The variables for total flight time, difference in flight levels and speed difference between the fastest and slowest aircraft in the sector are still significant and of approximately the same value as that for the model without serial autocorrelation.
- The variables for the number of neighbouring sectors from which aircraft enter or to which aircraft exit show a major change. The number of neighbouring sectors to which aircraft exit is no longer significant, whilst the variable for the number of sectors from which aircraft enter a sector is just significant at the 5% level, with a parameter value similar to that of the model with no serial correlation. Therefore, if these particular variables are considered as some surrogate of spatial aspects in the data, it seems that once temporal correlation is corrected for, the spatial effects reduce.
- The variables for aircraft entry in the different phases of flight are significant. It is worth noting that whilst the parameter values for aircraft entry in cruise and descend have similar values for both models, once temporal autocorrelation is accounted for, the parameter value for aircraft entering in climb doubles from 12 seconds to 24 seconds. However, none of the variables for aircraft exit in different phases of flight are significant.

Finally, whilst an AR(1) error term has been fitted to the panel data model to account for temporal autocorrelation, the ρ value of 0·28 for the linear model and the modified Bhargava et al., 1982 statistic indicates the presence of some residual temporal correlation. It may be therefore that more complex AR(q) error terms are required to better account for the temporal autocorrelation.

10. MODEL PREDICTION. The efficacy of using the cross-sectional time series technique lies in its ability to accurately predict the workload in a sector at different times of the day, given the appropriate set of significant variables. The parameter estimates of the model from the panel data can be subsequently used for predicting the workload in a sector throughout the day. Figure 6 shows the predicted workload obtained using the parameters for the significant variables from the model with no serial correlation compared to "actual" workload recorded by RAMS for two sectors. This graphical analysis seems to indicate a good model fit, i.e. goodness of fit, with the predicted workload curve mirroring the actual workload curve closely.

When the data is considered for all the 46 sectors for 20 hours, a plot of actual workload recorded against the estimated workload gives an indicator of the measure of accuracy of the model. Figure 7 shows this plot, along with a 45 degrees line. This line indicates how closely the model predicts the actual workload, since if the actual and predicted workloads were always equal, all points in this graph would lie along this line. This figure shows that the model estimates reasonably well the actual

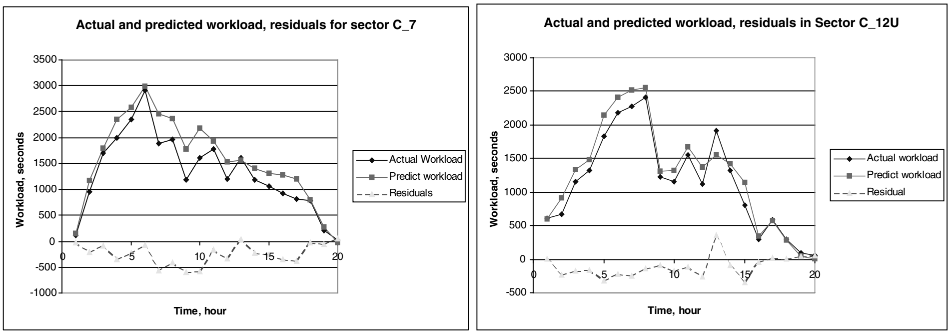

Figure 6. Actual and predicted workload for sectors C_7 and C_12U in the CEATS airspace region for the 20-hour day.

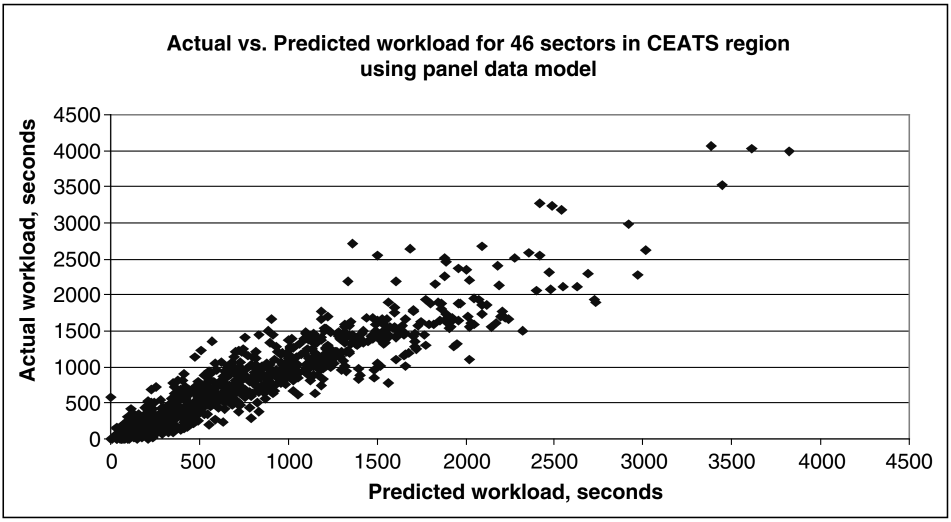

Figure 7. The graph of actual vs. predicted workload for the 46 sectors throughout the 20-hour day in the CEATS region.

workload, though anomalies at high workloads should be investigated. Therefore it seems that a subset of about ten significant variables, with their estimated parameter values, can adequately predict the simulated workload obtained using RAMS in any given sector in the CEATS region in any given hour. However, given the bespoke nature of ATC in different airspace regions of Europe, there may be a need to consider other variables. Anomalies in the results could be due to possible model misspecification, requiring the need to include quadratic variables to account for interactions.

11. CONCLUSION.

En route airspace capacity in Europe is primarily determined by controller workload. This paper has indicated that the cross-sectional time-series analysis of a simulated region of airspace can be a useful method by which to study the factors affecting controller workload throughout the day, and to predict this workload. It has also highlighted that the variables that best describe the controller workload in the peak hour seem to differ from those throughout the day. This is important since there appears to be a "peak spreading" effect in daily traffic rather than pronounced peaks in European air traffic. Given the strong predictive abilities of the analysis, there is a need to undertake further analysis of this method to ensure its robustness. Finally it should however be noted that the research presented here has been based on simulated data, i.e. an analytical model based upon the output of a simulation model. As such, this is a good initial step in obtaining the drivers of workload and operational data is needed for thorough validation of the results, assuming enough of such data could be obtained for statistical adequacy.

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