Modeling and Predicting Mental Workload in En Route Air Traffic Control: Critical Review and Broader Implications

Shayne Loft, Penelope Sanderson, Andrew Neal, and **Martijn Mooij,** The University of Queensland, Brisbane, Australia

Objective: We perform a critical review of research on mental workload in en route air traffic control (ATC). We present a model of operator strategic behavior and workload management through which workload can be predicted within ATC and other complex work systems. **Background:** Air traffic volume is increasing worldwide. If air traffic management organizations are to meet future demand safely, better models of controller workload are needed. **Method:** We present the theoretical model and then review investigations of how effectively traffic factors, airspace factors, and operational constraints predict controller workload. **Results:** Although task demand has a strong relationship with workload, evidence suggests that the relationship depends on the capacity of the controllers to select priorities, manage their cognitive resources, and regulate their own performance. We review research on strategies employed by controllers to minimize the control activity and information-processing requirements of control tasks. **Conclusion:** Controller workload will not be effectively modeled until controllers' strategies for regulating the cognitive impact of task demand have been modeled. **Application:** Actual and potential applications of our conclusions include a reorientation of workload modeling in complex work systems to capture the dynamic and adaptive nature of the operator's work. Models based around workload regulation may be more useful in helping management organizations adapt to future control regimens in complex work systems.

INTRODUCTION

With the rapid advancement of technology, complex work systems have evolved in which operators must adapt their decision making and performance in the face of dynamic, ever-changing environments, concurrent task demands, time pressure, and tactical constraints (Moray, 1997; Sheridan, 2002). The assessment and prediction of the mental workload associated with operating such complex systems has long been recognized as an important issue (e.g., Gopher & Donchin, 1986; Moray, 1979). Mental workload – or just workload – is the general term used to describe the mental cost of accomplishing task requirements (Hart & Wickens, 1990; Wickens, 1992). Workload varies as a function of task demands placed on the human operator and the capacity of the operator to meet those demands (Gopher & Donchin, 1986; Hopkin, 1995). High levels of workload occur when task demands exceed operator capacity.

Research efforts in complex work systems such as piloting (e.g., Wilson, 2002), unmanned aerial vehicle control (e.g., Dixon, Wickens, & Chang, 2005), anesthesiology (e.g., Leedal & Smith, 2005), railway signaling (e.g., Pickup et al., 2005), and automobile driving (e.g., Recarte & Nunes, 2003) have focused on identifying factors that influence mental workload and techniques for measuring it. In contrast, in the current paper we develop a theoretical model of operator strategic behavior and workload management, within the context of en route air traffic control (ATC), through which task-related workload can be predicted within complex work systems. The model we present takes into account the changing task priorities and management of resources by operators as well as the feedback that operators receive in response to their input. In the next section, we explain the nature of

Address correspondence to Shayne Loft, ARC Key Centre for Human Factors and Applied Cognitive Psychology, University of Queensland, Brisbane 4072, Australia; lofts@psy.uq.edu.au. ***HUMAN FACTORS,*** Vol. 49, No. 3, June 2007, pp. 376–399. DOI 10.1518/001872007X197017.

the work performed by en route air traffic controllers (ATCos) and provide an overview of our approach.

OVERVIEW

Controlled airspace is divided into sectors. An en route sector is a region of airspace that is typically situated at least 30 miles (~48 km) from an airport for which an associated ATCo has responsibility. ATCos have to accept aircraft into their sector; check aircraft; issue instructions, clearances, and advice to pilots; and hand aircraft off to adjacent sectors or to airports. The radar screen displays characteristics of the sector (e.g., boundaries and airways), the spatial position of aircraft, and vital flight information (identifiers, altitude, speed, flight destination). When the aircraft leaves the airspace assigned to the ATCo, control of the aircraft passes on to ATCo controlling the next sector (or to the tower ATCo). As is typical in many real-world complex systems, this environment imposes multiple concurrent demands on the operator. As Gronlund, Ohrt, Dougherty, Perry, and Manning (1998) described it, "In the en route air traffic control environment (involving the high-speed and high-altitude cruise between takeoff and landing), the system that confronts the air traffic controller comprises a large number of aircraft coming from a variety of directions, at diverse speeds and altitudes, heading to different destinations. Like most complex, dynamic systems, this one cannot be periodically halted while the controller takes a brief respite" (p. 263).

ATCos have two main goals. The primary goal is to ensure that aircraft under jurisdiction adhere to International Civil Aviation Organization (ICAO) mandated separation standards. For example, one of the most common separation standards requires that aircraft under radar control be separated by at least 1,000 feet vertically (2,000 feet above 29,000 feet, unless reduced vertical separation minima apply) and 5 nautical miles horizontally. The secondary goal is to ensure that aircraft reach their destinations in an orderly and expeditious manner. These goals require the ATCo to perform a variety of tasks, including monitoring air traffic, anticipating loss of separation (i.e., conflicts) between aircraft, and intervening to resolve conflicts and minimize disruption to flow. (For an extensive compilation of the tasks and goals of en route control, see Rodgers & Drechsler, 1993.)

Total world airline scheduled passenger traffic in terms of passenger-kilometers is projected to grow at an annual average rate of 4.4% over the period 2002 to 2015, according to forecasts prepared by the ICAO (2004). In the United States alone, the number of aircraft handled by ATC centers is expected to increase from 46.2 million in 2004 to more than 60.2 million in 2016 (Federal Aviation Administration, 2005). To accommodate predicted traffic growth there is a need to increase en route airspace capacity through the introduction of new air traffic management systems (e.g., free flight) or the adaptation of existing airspace designs (e.g., sector boundaries), controller tools (e.g., conflict resolution), and procedures (e.g., reduced separation minima). The consensus among research and operational communities is that it is important to understand the factors that drive mental workload if they are to improve airspace capacity (Christien, Benkouar, Chaboud, & Loubieres, 2003; Majumdar, Ochieng, McAuley, Lenzi, & Lepadatu, 2004).

Most research has focused on identifying characteristics of the air traffic picture that create task demand for ATCos (e.g., Grossberg, 1989; Kirwan, Scaife, & Kennedy, 2001; Manning, Mills, Fox, & Pfleiderer, 2001). These characteristics include the number of aircraft in transition though a sector, the number of aircraft changing altitude, and the number of potential conflicts. Several research groups have attempted to predict mental workload on a moment-to-moment basis by using linear combinations of task demand factors as predictors. The resulting sets of task demand factors are known as *dynamic density metrics.* Studies have shown that the dynamic density of the airspace at a given moment accounts for approximately half the variance in workload at that point in time (e.g., Kopardekar & Magyarits, 2003; Laudeman, Shelden, Branstrom, & Brasil, 1998). In psychological terms, this represents relatively strong prediction. In practical terms, however, a significant proportion of variance remains unaccounted for. Furthermore, one goal of workload modeling is to allow ATC providers to predict workload levels ahead of time in order to allow them to put workload management strategies in place. For example, this may include splitting a sector or introducing flow restrictions. However, to date, dynamic density metrics have been unable to accurately predict ATCo workload ahead of time (Kopardekar & Magyarits, 2003; Majumdar & Ochieng, 2002;

Masalonis, Callaham, & Wanke, 2003). Many researchers argue that these limitations stem from the fact that there is no simple linear relationship between task demand and workload (e.g., Athènes, Averty, Puechmorel, Delahaye, & Collet, 2002; Chatterji & Sridhar, 2001). Moreover, these researchers view workload as an emergent property of the complex interaction between the ATCo and the air traffic situation, rather than as a simple outcome of task demand inputs at a single point in time.

The approach to predicting ATCo mental workload that is presented in the current paper is in line with these views. According to Sperandio (1971), workload is not something imposed upon a passive ATCo but, rather, is something the ATCo actively manages. He proposed a model in which changes in strategy (primarily resource management) allow ATCos to regulate how task demands are transformed into workload, thus keeping workload within acceptable limits. In a paper that deserves to be better known, Rouse, Edwards, and Hammer (1993) took a similar view, modeling workload as a feedback control process driven by subjective mental workload. Several current research groups agree with Sperandio's (1971) view that a relationship between task demand and workload can be better understood by considering how ATCos use strategies to manage their resources and regulate their workload (Athènes et al., 2002; Averty, Collet, Dittmar, Vernet-Maury, & Athènes, 2004; Cullen, 1999; Hilburn, 2004; Histon & Hansman, 2002; Majumdar et al., 2004). Another key aspect of Sperandio's (1971) approach is that the effect of ATCo control actions on the system is fed back to the ATCo, such that future task demands are actively regulated by the ATCo (Pawlak, Brinton, Crouch, & Lancaster, 1996).

In the current paper, we present a model of mental workload that puts ATCos in the loop with air traffic events, reacting to the consequences of their own proactive behavior. Without denying the validity of the task demand approach, we argue that the link between task demand and workload is largely connected to the manner in which ATCos manage their resources. We begin by outlining a general model of workload in ATC and contrast it with previous approaches. We then review task demand research in ATC. A characteristic of this research that limits its interpretability is the extremely large list of methods and task demand factors that have been reported. (For exhaustive reviews, see Hilburn, 2004; and Mogford, Guttman, Morrow, & Kopardekar, 1995.) The model presented in this paper provides a framework for integrating this literature and studying its potential strengths and shortcomings. We then turn our attention to the smaller body of research that has focused on ATCo control strategies (e.g., Amaldi & Leroux; 1995; Histon & Hansman, 2002) and to task models that have been built to simulate the performance of ATCos (e.g., Callantine, 2002; Leiden, Kopardekar, & Green, 2003). Finally, we review models in which researchers have attempted to integrate task demands with human performance models in order to predict workload (e.g., Averty et al., 2004; Cullen, 1999).

MENTAL WORKLOAD MODELING ARCHITECTURES

In this section we outline different modeling architectures that have been used to understand ATCo mental workload. At the end, we present the architecture that guides our review of the literature that follows.

Common Architectures

A prevalent model in ATC mental workload research is that different properties, or task demands, of the air traffic situation will pose problems of different levels of complexity to the ATCo and, depending on the ATCo's skill, experience, and strategy, will produce different levels of subjective workload. This is effectively an open-loop model, as shown in Figure 1. Variants of this general open-loop architecture have been used to model sources of ATCo workload. For example, Hilburn and Jorna's (2001) model shows system factors combining to create task demand, which, in accordance with operator factors such as skill, strategy, and experience, will lead to some degree of workload. Similarly, Mogford et al.'s (1995) model depicts a relationship between source factors (objective complexity, air traffic patterns, sector characteristics) and workload being mediated by quality of equipment, individual differences, and ATCo strategies. Both these models acknowledge that ATCo strategy can influence workload. Nevertheless, researchers using these models as frameworks have tended to focus on whether individual aspects of the ATC environment affect workload. We argue that the tendency to seek input-output relations ("does increasing the number of aircraft

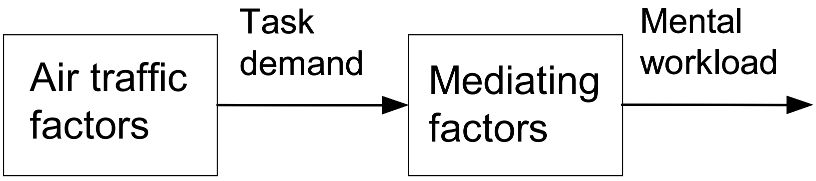

Figure 1. Generic form of an open-loop model of mental workload implicitly adopted in many studies of ATCo mental workload.

increase workload?" or "how does strategy influence the impact of the number of aircraft on workload?") fails to take into account fully the goals and management of resources by the ATCo and feedback that the ATCo receives from the system in response to his or her input.

Sperandio's Architecture

It is interesting to contrast the aforementioned models with that of Sperandio (1971), shown in Figure 2. Again, task demand is on the left and mental workload on the right. Consistent with the previous two models, Sperandio (1971) proposed that ATCo strategy is an intervening variable between task demand and the work achieved and that the ATCo selects strategies to keep mental workload within acceptable limits. However, in contrast to the models mentioned in the previous paragraph, the Sperandio (1971) model includes two feedback control loops. First, variation in mental workload resulting from work methods has, through feedback, a regulating effect on the choice of work methods (Feedback Loop 1). Second, the work method used in response to perceived task demands regulates the task demand encountered in the future (Feedback Loop 2). Sperandio (1971) emphasized that it is the change in workload, not the change in task demand, that explains the change in strategy. The change in strategy changes what information is extracted from the airspace and thus affects workload. The relationship among task demand, strategy, and workload is adaptive and so can be shown only in a feedback control diagram, as shown in Figure 2. This position is consistent with that of Rouse et al. (1993) but is in contrast to much subsequent research in which mental workload is predicted from objectively measured characteristics of the airspace, tuned by strategy and other factors.

A Systems Approach to Modeling Mental Workload

The basis of our approach is that the ATCo is in a continuous relationship with a dynamic world and is an adaptive element in that world (Athènes et al., 2002; Pawlak et al., 1996; Sperandio, 1971). As a result, mental workload cannot be a function solely of task demands; it is also a function of the strategy the ATCo uses to manage traffic and whether the strategy, once invoked, has provided

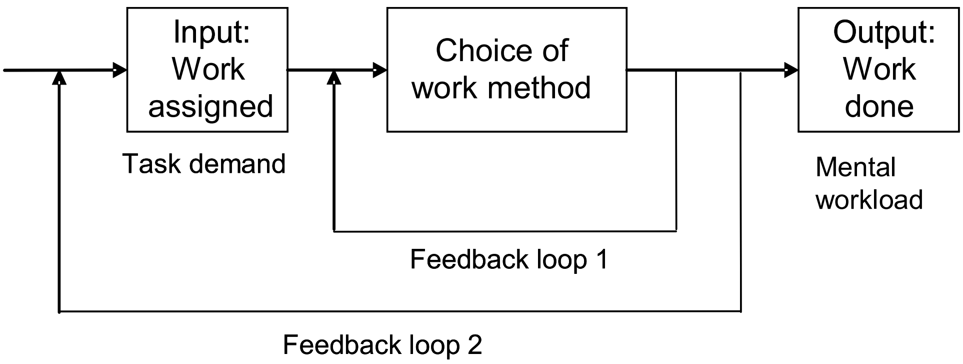

Figure 2. Sperandio's (1971) closed-loop model of ATCo mental workload in which actual work done influences choice of work methods and amount of work accepted. Task demand is equivalent to work to be done. Variation of operator's strategies and regulating effects on workload, J. C. Sperandio, *Ergonomics,* (1971), Taylor & Francis Ltd, adapted by permission of the publisher (Taylor & Francis Ltd, http://www.tandf.co.uk/journals).

a comfortable level of control over task demands. In the next section, we work through the ATC literature with the help of the model that is shown in Figure 3. In an adaptation of Sperandio's (1971) model, our model represents two control loops that govern ATCo activity: first, the management of workload by the internal reorganization of priorities leading to a different strategy; and second, the management of workload by explicit control of the airspace. The work of the ATCo occupies the shaded part in the centre of Figure 3, whereas the world that the ATCo controls is shown in the perimeter.

The model in Figure 3 simplifies the world that the ATCo controls. It shows two aircraft, which is the minimum needed to indicate that the ATCo is concerned with managing relationships among aircraft rather than controlling single aircraft in isolation. One aircraft is at the top of Figure 3 and the other at the bottom. Each aircraft receives instructions from the ATCo (see plus signs [+] on links into adder symbols at top right and bottom right of Figure 3). The pilot considers the difference between the instruction and the aircraft's current flight profile (see minus sign [–] on feedback loops coming into rightmost adder symbols) and makes an appropriate adjustment to the aircraft's flight profile. The aircraft's new flight profile is combined with the flight profile of all other aircraft (see two + signs entering adder at left) and becomes the task demand fed back to the ATCo. The ATCo can take action to change future task demand fed back through the system (e.g., by accepting aircraft early or by putting aircraft in a holding pattern) or he or she can change future task demand with cognitive strategies (e.g., by considering a set of aircraft as one for purposes of control).

The ATCo remains aware of work to be done by monitoring present task demands (see left of Figure 3). The work to be done is translated into actual work done through the control activities performed. As Figure 3 suggests, a set of control activities can be classified as a strategy. A strategy can be described as a specific class of air traffic management that achieves one or more objectives (e.g., safety, orderliness, expeditiousness) with a certain investment of time and effort. Selection

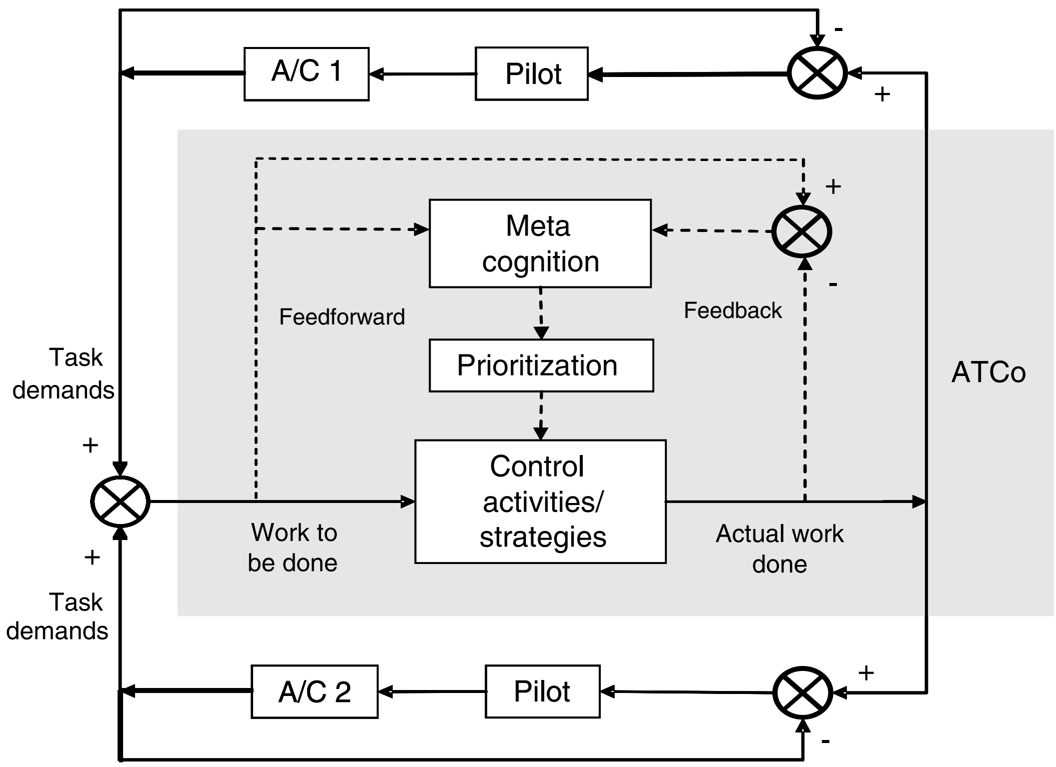

Figure 3. Model of ATCo activity in which strategy is controlled through feedback and feedforward information about mental workload. Work to be done represents how objective task demands are mentally represented by the ATCo.

among strategies is driven by the relative priority of the ATCo's objectives as the work to be done evolves over time (Kallus, Van Damme, & Dittman, 1999; Kirwan & Flynn, 2002; Niessen, Eyferth, & Bierwagen, 1999). The strategy chosen will lead to a certain quality of control over the situation, which will often reflect subjective time pressure. For example, the contextual control model (COCOM) of Hollnagel (2002) and Hollnagel and Woods (2005) distinguishes strategic, tactical, opportunistic, and scrambled control as the result of an operator's subjective judgment of the relationship between time available for action (Ta) and the time required to evaluate the situation (Te), select a response (Ts), and perform the response (Tr). In their COCOM model, strategic and tactical control are mostly proactive, whereas opportunistic and scrambled control are mostly reactive. An ATCo will work to achieve strategic control and avoid scrambled control as much as possible.

Figure 3 indicates that prioritization drives control activities/strategies. Prioritization refers to the professional set of values that guide control of air movements at any point, such as safety, orderliness, and expeditiousness. Prioritization, in turn, is driven by metacognitive factors such as awareness of time available to perform tasks, anticipation of future difficulties, and the ATCo's knowledge of his or her capacity. However, we do not assume that this is a conscious process. Instead, prioritization is a consideration satisfied directly or indirectly through control action. The strategy may be a learned response that is not open to introspection, and it may not require explicit consideration of safety, orderliness, or expeditiousness. However, this does not remove the fact that strategies will always reflect some balance of priority among safety, orderliness, and expeditiousness. The selection of strategy will be logically guided by the appropriate priority even if the priority is not consciously accessed.

Focusing in particular on time, Schmidt (1978) predicted ATCo mental workload with a queuing theory model based on the relationship between the frequency of observable tasks that require decisions/actions and the time required to make these decisions/actions. More recently, Hendy, Liao, and Milgram (1997) used a simulated ATC task and modeled overall workload as a univariate function of time pressure. Time pressure, in turn, was modeled as the ratio of time available to time required, also expressible as the ratio of the information-processing rate demanded by a task and the maximum information-processing capacity of the ATCo. Performance data were well matched by the model. Most recently, Rantanen and Levinthal (2005) demonstrated that an ATCo's time to first intervention in resolving conflicts was faster when the ratio of time to act to the duration of a window of opportunity for action was small – in other words, when there was less discretionary time.

The dashed lines within the shaded ATCo part of Figure 3 indicate that metacognition can be influenced by both feedforward and feedback signals. Looking at feedforward (at left), the ATCo may be aware that a large number of aircraft are about to enter the sector and thus adjusts his or her strategy for handling traffic already on frequency. Looking at feedback (at right), the ATCo may be aware that the quality of actual work done may have been compromised by time pressure and thus adjust priorities toward achieving safety at the possible expense of expeditiousness (e.g., by rearranging the trajectories of aircraft in order to minimize monitoring and coordination requirements). The adder to the right of metacognition in Figure 3 shows that the ATCo may notice differences between the work to be done and the actual work that is getting done, which will also trigger a metacognitive response. For example, the ATCo may realize that a heavy communication load is making him or her fall behind in dealing with work to be done, yet an even heavier communication load is anticipated. A rearrangement of priorities may offer a control strategy that has a less intense communications load. In these ways the model in Figure 3 represents the fact that ATCos behave and react to the consequences of their behavior – in respect both to the perceived discrepancy between current goals and system state and to the ATCo's understanding of his or her own capacity – and that these processes drive mental workload.

In the following sections we review research on the relationships between task demand and mental workload and between operator capacity and mental workload. Then we review research that combines the two in ways that are at least partially consistent with the model in Figure 3.

TASK DEMANDS AND MENTAL WORKLOAD

Research concerning the relationship between task demand and mental workload has had a long history, dating back more than 40 years (Arad, 1964; Couluris & Schmidt, 1973; Davis, Danaher, & Fischl, 1963; Hurst & Rose, 1978; Schmidt, 1976). This research has focused on uncovering properties of the air traffic environment that contribute to cognitive complexity and, via tuning factors such as skill, strategy and experience, result in workload (see Figure 1). The task demand literature, in its own right, provides a solid basis from which to model the complexity of task demands (work to be done) in the ATC system. Researchers have expended great effort in developing predictive models based on task demand, and the fact that these models have been able to account for significant variance in ATCo workload warrants a state-of-the-art review and synthesis. We maintain, however, that focusing only on task demand overlooks the reciprocal interactions presented in Figure 3. Subsequently, we examine whether the task demand literature explicitly or implicitly models these aspects of control, and we outline contradictions in the literature that result from the failure to take a systems view.

Our review of task demand research is summarized in Table 1. The material is drawn from government and contractor technical reports, operational reviews, journal articles, and book chapters. Much material originates in the United States and Europe, primarily from the Federal Aviation Administration, the National Aeronautics and Space Administration (NASA), and the European Organisation for the Safety of Air Navigation (EUROCONTROL). During the review process, we found that several aspects of task demand research limited its interpretability. Two valuable surveys of research relating to task demand (Hilburn, 2004; Mogford et al., 1995) do not explicitly address these issues. These constraints, and how we dealt with them, will be briefly discussed next.

First, systematic comparison among studies was complicated by the wide variety of research methodologies reported. As presented in Table 1, these methodologies include *knowledge elicitation techniques* such as verbal protocol analysis (e.g., Pawlak et al., 1996), *experiments* in which researchers made predictions a priori about how mental workload will vary with systematic manipulation of task demand (e.g., Boag, Neal, Loft, & Halford, 2006), and *correlational studies* in which researchers extracted values for task demand factors from flight data and correlated these values with workload on a post hoc basis (e.g., Kopardekar & Magyarits, 2003). A second characteristic of task demand research that limits cross-study comparison is the wide variety of workload measures used. An evaluation of the advantages and disadvantages of each approach is beyond the scope of this paper (see Farmer & Brownson, 2003; Hilburn & Jorna, 2001). However, Table 1 categorizes studies according to the workload criterion employed. As is evident from Table 1, the measurement of workload is far from uniform.

Table 1 reveals that most studies have focused on identifying *traffic factors.* Traffic factors reflect the instantaneous distribution of air traffic in a sector in terms of both the number of aircraft and the complexity of their relationships. However, ATCos can actively regulate the mental workload associated with traffic factors by using economical control strategies. Researchers such as Hilburn (2004) and Histon and Hansman (2002) identified two further factors that influence the choice and effectiveness of ATCo control strategies and which are generally independent from traffic factors. *Airspace factors* reflect the underlying structural properties of the airspace (e.g., number of crossing altitude profiles). Airspace factors constrain the relationship between traffic factors and workload by shaping the evolution of air traffic and creating predictable air traffic patterns that can be exploited by ATCos. *Operational constraints* reflect operational requirements (e.g., restrictions of available airspace) that place restrictions on ATCo strategy and control action.

Traffic Factors Predicting Mental Workload

Task demand research has typically focused on explicit properties of the distribution of aircraft that predict mental workload and are computed in real time using radar track data or derivations thereof. Of all the traffic factors, the aircraft count, or the number of aircraft under control, is the most powerful predictor of workload (e.g., Hurst & Rose, 1978; Kopardekar & Magyarits, 2003; Manning et al., 2001). High aircraft count leads to an increase in workload because it increases the monitoring, communication and coordination required to handle aircraft in a safe, orderly, and expeditious manner.

Density factors are derivatives of traffic count that measure the horizontal and vertical distances between aircraft and the way in which these distances change with time. Various measures of traffic density have been developed, including the average horizontal (or lateral) separation distances between aircraft (Chatterji & Sridhar, 2001) and aircraft counts divided by sector volumes (Kopardekar & Magyarits, 2003). These density measures assume, perhaps erroneously, that all aircraft in close proximity are noticed by the ATCo and therefore exert some influence on mental workload. In reality, the influence of aircraft density on workload will depend on what the aircraft are doing in relation to each other – for example, whether they are converging or diverging. For this reason, density factors based on the minimum separations between pairs of aircraft are more sensitive (Chatterji & Sridhar, 2001). Close future minimum separation between an aircraft pair will undoubtedly capture ATCo attention because of the likelihood of a separation violation, reducing the ATCo's capacity to attend to other control tasks.

Although traffic count and density adequately reflect the number of routine aircraft-associated tasks that an ATCo has to perform within a certain time frame, the complexity of air traffic is important in determining the difficulty of the tasks or events handled and thus the resulting mental workload. ATCos report that they can handle relatively large volumes of traffic if the aircraft are flying on regular routes and the flow is orderly (e.g., Amaldi & Leroux, 1995; Mogford et al., 1995). In contrast, small volumes of traffic can lead to overload if aircraft interact in complex ways (Kallus, Van Damme, & Dittman, 1999; Mogford et al., 1995). Complexity factors fall into two categories. The first are commonly referred to as *aircraft transition* factors and capture changes in an aircraft's state in any of the three axes of altitude (e.g., Lamoureux, 1999), speed (e.g., Kopardekar & Magyarits, 2003), or heading (e.g., Laudeman et al., 1998). Performance mix of aircraft is also an important aircraft transition factor (Schaefer, Meckiff, Magill, Pirard, & Aligne, 2001). In order to calculate the minimum separation between two aircraft in altitude transition, the ATCo needs to know how fast the aircraft will climb (or descend) relative to each other. Presumably, this job would be made harder by increased variability in performance profiles.

The second set of complexity factors relates to the number and nature of *potential conflicts* within a sector. Potential conflicts emerge from the combination of density and transition factors present at any time. The influence of potential conflicts on mental workload depends on their specific properties. For example, Boag et al. (2006) developed a "transitions metric" for assessing the difficulty of judging whether a pair of aircraft will be in lateral and vertical conflict at the same time. If two aircraft are on converging flight paths, and are both maintaining the same level, then the ATCo simply needs to assess whether they will violate the lateral separation standard. This problem is relatively simple because the ATCo need consider only one transition (the transition into lateral conflict). However, if the aircraft are changing levels, then the ATCo must assess when the aircraft will violate and regain separation in one dimension and also whether the aircraft will be in conflict in the other dimension at the same time. Up to four transitions (into and out of lateral and vertical conflict) may be possible. The Boag et al. (2006) transitions metric accounted for significant amounts of variance in ATCos' ratings of complexity and workload. Imminent violations of separation also increase workload (Chatterji & Sridhar, 2001). The time available for an ATCo to detect and respond to a potential conflict affects how difficult the conflict is to resolve. A conflict that develops quickly gives the ATCo only a limited time to act, creating significant time pressure. Conflicts in close proximity to sector boundaries (e.g., Pawlak et al., 1996) and/or high numbers of surrounding aircraft (e.g., Kopardekar & Magyarits, 2003) also constrain how conflicts can be resolved, reducing the number of options for maneuvering.

Combining Task Demand Factors Into Dynamic Density Metrics

Several research groups (Kopardekar & Magyarits, 2003; Laudeman et al., 1998; Masalonis et al., 2003) have used regression models to identify sets of factors that best predict mental workload and have created algorithms by weighting these different factors according to their predictive power. The resulting algorithms are commonly referred to as *dynamic density metrics.* Dynamic density has been defined as "the collective effort of all factors, or variables, that contribute to sector-level air traffic control complexity or difficulty at any point in time" (Kopardekar & Magyarits, 2003, p. 1). The Laudeman et al. (1998) metric is perhaps the best known, describing dynamic density as the sum of the density of traffic weighted by the number of changes in speed, heading, and

TABLE 1: Studies Predicting ATCo Mental Workload: Methods of Measurement and Summaries of Results

Authors	Method	Measures	Task Demand Factors	Systems View
Arad (1964)	Correlational	ATCo activity	Traffic, airspace, and operational constraints	Sector boundaries aligned with standard flows reduce the time pressure of control activities.
Boag et al. (2006)	Experiment: part-task simulation	MW ratings Complexity ratings	Traffic	The number of conflict boundary transitions increases MW because ATCos cannot reduce information set.
Buckley, DeBaryshe, Hitchner, & Kohn (1983)	Experiment: full task simulation	ATCo activity	Traffic and airspace	Airspace factors interact with traffic factors in determining MW; ATCos use airspace structure to simplify air traffic.
Chatterji & Sridhar (2001)	Correlational: dynamic density	MW ratings	Traffic	Model incorporates cognitive aspects (e.g., time pressure) into choice of traffic complexity factors.
Couluris & Schmidt (1973)	Experiment: Full task simulation	ATCo activity	Airspace	Using ATCo activity as measure of MW fails to take into account the intent of control action.
Davis et al. (1963)	Experiment: Full task simulation	ATCo activity	Traffic	Using ATCo activity as measure of MW fails to take into account the intent of control action.
Galster et al. (2001)	Experiment: Part-task simulation	MW ratings Secondary task	Traffic	Delays in conflict detection impose constraints on conflict resolution.
Histon & Hansman (2002)	Knowledge elicitation: live observation and interview	Complexity ratings	Traffic, airspace, and operational constraints	Airspace factors interact with traffic factors in determining MW; ATCos use airspace structure to simplify air traffic.
Hurst & Rose (1978)	Correlational: full task simulation	ATCo activity	Traffic	Using ATCo activity as measure of MW fails to take into account the intent of control action.
Kirwan et al. (2001)	Knowledge elicitation: group judgment	Complexity ratings	Traffic, airspace, and operational constraints	ATCos use airspace structure to simplify air traffic.
Kopardekar & Magyarits (2003)	Correlational: unified dynamic density	Complexity ratings	Traffic and airspace	Airspace factors play an important role in predicting MW across sectors.
Lamoureux (1999)	Experiment: part-task simulation	MW ratings	Traffic	MW is linked to the mental calculations and projections involved in managing groups of A/C.
Laudeman et al. (1988)	Knowledge elicitation: interview Correlational: dynamic density	ATCo activity	Traffic	Acknowledged that variation in the intent of ATCo control action can influence the relationship between ATCo activity and MW.

Manning et al. (2001)	Correlational: ATCo activity from routine flight data	MW ratings	Traffic	ATCo activity does not significantly predict MW over and above traffic count; fails to take into account the intent of control action.
Manning, Mills, Fox, Pfleiderer, & Mogilka (2002)	Correlational: ATCo activity from routine flight data	MW ratings	Traffic	No. and type of ATCo communications do not significantly predict MW; fails to take into account the intent of ATCo communications.
Masalonis et al. (2003)	Knowledge elicitation: interview Correlational: dynamic density	Complexity ratings	Traffic, airspace, and operational constraints	Metric unable to accurately predict MW ahead of time; fails to take into account the influence of ATCo control strategy/activity on future task demand that is fed back through system.
Metzger & Parasuraman (2001)	Experiment: part-task simulation	MW ratings Secondary task	Traffic	Delays in conflict detection impose constraints on conflict resolution.
Mogford et al. (1993)	Knowledge elicitation: rating and ranking	Complexity ratings	Traffic, airspace, and operational constraints	Airspace factors and operational constraints play a role in shaping the relationship between traffic factors and MW.
Pawlak et al. (1996)	Knowledge elicitation: verbal protocol technique	MW ratings Complexity ratings	Traffic, airspace, and operational constraints	Emphasis on factors that impact on the cognitive activity of ATCos, as opposed to behavioral indicators (e.g., ATCo activity).
Schaefer et al. (2001)	Knowledge elicitation: interview	Complexity ratings	Traffic, airspace, and operational constraints	Airspace factors interact with traffic factors in determining MW.
Stein (1985)	Experiment: full task simulation	MW ratings	Traffic	No. of handoffs (inbound and outbound) predict MW; however, highly correlated with A/C count.
Wyndemere, Inc. (1996)	Knowledge elicitation: critical decision Correlational: dynamic density	MW ratings	Traffic and airspace	Metric included several airspace factors.

Note. MW = mental workload; A/C = aircraft.

altitude; the proximity of aircraft; and the time until predicted conflicts. This metric accounted for 22% of the variance in ATCo activity (a proxy for workload) not predicted by aircraft count. Kopardekar and Magyarits (2003) incorporated 23 factors from four published dynamic density metrics to form a composite metric. This unified dynamic density accounted for 39% of the variance in ATCo complexity ratings, significantly more than aircraft count alone.

Airspace Factors and Operational Constraints Predicting Mental Workload

Airspace factors and operational constraints are key contributors to ATCo task demand and mental workload (Histon & Hansman, 2002; Kirwan et al., 2001). Airspace factors refer to the underlying structural properties of the airspace, whereas operational constraints refer to temporary variations in operational conditions within the airspace. Airspace factors constrain the relationship between traffic factors and workload by shaping the evolution of air traffic and creating predictable air traffic patterns. Knowledge of these patterns lets the ATCo use information-processing strategies that simplify air traffic management. Furthermore, temporary variations in operational conditions, such as communications limitations (Mogford, Murphy, Yastrop, Guttman, & Roske-Hofstrand, 1993), can restrict ATCo control action and strategy.

Studies examining airspace factors have found that the size of a sector can influence the mental workload imposed by traffic factors (Arad, 1964; Histon & Hansman, 2002). On the one hand, a larger sector size will typically increase the number of aircraft in the sector and the number of potential events that require attention. On the other hand, events evolve faster in smaller sectors, and limited space in a sector can reduce the options for conflict resolution. Increased number of available flight levels can reduce workload because they allow ATCos to maintain separation using vertical separation (Histon & Hansman, 2002; Kirwan et al., 2001). Traffic events occurring close to the outside of sector boundaries are important further determinants of workload (Couluris & Schmidt, 1973; Histon & Hansman, 2002) because they can cause the ATCo's "area of regard" to be greater than the official dimensions of the sector. Aircraft events occurring outside sector boundaries require attention because they can affect aircraft currently in the sector, increasing the complexity of coordination (handoffs, point outs) with adjacent ATCos (e.g., Kirwan et al., 2001; Mogford et al., 1993). However, the presence of well-defined ingress and egress points (Histon & Hansman, 2002) lets ATCos anticipate problems, thus reducing workload.

The number, orientation, and complexity of standard flows also influence the mental workload imposed by traffic factors (Histon & Hansman, 2002; Schaefer et al., 2001). Standard flows are aircraft flow patterns that emerge from underlying airway structure, standardized procedures, and other regular constraints such as ingress and egress points. ATCos use their knowledge of standard flows to create important structure-based abstractions that simplify the management of air traffic (Histon & Hansman, 2002). For example, ATCos can simplify the search process involved in conflict detection by focusing on known crossing points and/or known crossing altitude profiles between standard flows (Histon & Hansman, 2002; Pawlak et al., 1996). Knowledge of these "hot spots" can reduce the workload associated with managing air traffic (Amaldi & Leroux, 1995; Kallus, Van Damme, & Dittman, 1999).

Several operational constraints place restrictions on ATCo control action. For example, restrictions on available airspace can result from convective weather, activation of special-use airspace, or aircraft in holding patterns (Kirwan et al., 2001; Mogford et al., 1993). Restrictions on available airspace increase the likelihood of separation violations. In addition, restricted airspace requires more precisely planned conflict resolution strategies. Procedural restrictions, such as miles-in-trail spacing, can also constrain traffic flow and conflict resolution strategies (Histon & Hansman, 2002; Pawlak et al., 1996).

Because of practical constraints, weightings for task demand factors are typically validated against one or only a few sectors (Histon & Hansman, 2002), limiting the variation observed in airspace factors and operational constraints. As a result, dynamic density metrics developed using specific sectors perform less effectively when extended to other sectors. However, two research groups have recently incorporated airspace factors into their metrics (Kopardekar & Magyarits, 2003; Masalonis et al., 2003). For example, the Kopardekar and Magyarits (2003) unified metric was developed across four sectors, and the metric performs differently across them. Nevertheless, comparisons across the different sectors revealed the contribution of airspace factors. Factors with significant predictive value included the altitude level of the sector (high vs. low), the structure of the airspace, and the size of the sector. It seems that if researchers wish to predict mental workload across sectors, then airspace factors and operational constraints will be important because they mediate the effect of traffic factors on workload. However, if researchers wish to predict workload within sectors, then the airspace factors and operational constraints become less important.

Summary and Assessment

Research focusing on task demand factors has shown that task demand accounts for a significant amount of variance in mental workload. We sought to develop our model of workload by investigating how different task demand factors might affect ATCos' selection of strategies for control and thus affect workload. However, this was made difficult by the lack of research examining how airspace structure and aircraft configuration relate to the selection of strategies for control, as depicted by the model in Figure 3. We argue that a significant limitation of the task demand approach is that it views the ATCo as a passive recipient of task demand. It does not explicitly take into account the fact that ATCos can actively take steps that change task demand, so as to keep workload at an acceptable level. Without denying the importance of task demands, we believe that workload might be more strongly connected to the ATCo's ability to manage his or her cognitive capacity, as described in the next section.

It is difficult to assess which aspects of task demand are most closely causally related to mental workload. One reason is multicollinearity. Ideally each traffic factor in a predictive model should contribute to workload relatively independently of other traffic factors, but this is seldom so. For example, in the Korpardekar and Magyarits (2003) unified metric, traffic count appears in several forms, such as sector volume (allowing more aircraft), number of aircraft, and aircraft count squared. However, the causal connection between traffic count and workload might be mediated by a number of complexity factors. For example, factors such as traffic density, number of speed transitions, number of conflicts, and number of aircraft near sector boundaries all depend on traffic count. In addition, under some conditions traffic count may carry the key causal connection because of the increase in low-level activities needed, whereas under other conditions complexity properties emerging from traffic count may carry the key causal connection because of the need to resolve complex traffic situations. In addition, many factors measuring the complexity of traffic situations are closely related. For example, the number of potential conflicts may depend on the number of speed, heading, and altitude variations. Overall, problems of multicollinearity make it difficult to determine how task demand affects workload. The problem with taking each possible task demand predictor and putting it in a regression equation is that the relative importance of each predictor depends on what other predictors have been included in the equation.

Even if the problem of multicollinearity can be resolved, task demand is still insufficient to account for mental workload. First, combinations of task demand factors rarely account for more than half the variance in workload or complexity ratings (Kopardekar & Magyarits, 2003; Majumdar & Ochieng, 2002). Although there may be objective and measurable features of sectors and aircraft flow, the difficulty of controlling traffic is the ATCo's subjective experience. If ATCos have alternative work methods for meeting increases in task demand, there will not necessarily be a linear relation between task demand and workload (Chatterji & Sridhar, 2001; Hilburn, 2004). Furthermore, task demand approaches do not take into account the ATCo's intent when extracting task demand predictors from radar track data. For example, changes in aircraft altitude are weighted so that they vary directly with workload. However, an ATCo could have various reasons for issuing a change in flight level, many of which may actually reduce workload (e.g., by ensuring separation).

A second reason that task demand is an insufficient basis for modeling mental workload is the need to predict mental workload ahead of time. It would be helpful to be able to predict probable aircraft trajectories from their flight plans and estimate the workload that the probable trajectories will impose on the ATCo. The problem is that task demands change dynamically; ATCos change the trajectories of aircraft when they intervene to ensure separation and establish arrival sequences. Furthermore, ATCos can reduce task demands in downstream sectors by carrying out tasks that would otherwise have to be done in that sector (giving descent clearances, implementing speed control, etc.). As has been found by Kopardekar and Magyarits (2003) and Masalonis et al. (2003), a workload model that does not take ATCo activity into account may not be able to predict workload accurately in the near future, such as 1 hr ahead.

A third reason for concern with task demand-driven models of mental workload is that such models are intended to predict whether workload will interfere with the performance or effectiveness of ATCos. The term *performance* refers to the ability of ATCos to carry out their tasks (maintain situation awareness, resolve conflicts, manage departure flows, etc.), whereas the term *effectiveness* refers to the outcomes that the ATCo achieves (i.e., the safety, orderliness, and efficiency of traffic flows: Neal, Griffin, Neale, Bamford, & Boag, 1998). Performance and effectiveness do not always decline as workload increases. Observations of ATCos in an operational environment suggest that whereas their ability to maintain an orderly and efficient flow of traffic does decrease as workload increases, their ability to perform tasks such as detecting and resolving conflicts and managing departures flows does not decline (Griffin, Neal, & Neale, 2000). It appears that the relationships among workload, performance, and effectiveness are complex and, possibly, contextually specific.

Human performance models provide a way of addressing these important issues. By building a human performance model that simulates how the ATCo carries out control tasks, it may be possible to generate more accurate predictions of aircraft trajectories and, hence, of future task demands. Furthermore, by taking into account strategies that ATCos use to minimize the amount of control activity required to meet their objectives, one can more accurately predict the effects of demands on both mental workload and performance.

OPERATOR CAPACITY, STRATEGIES, AND MENTAL WORKLOAD

As noted previously, and as Figure 3 suggests, mental workload emerges not only from task demands but also from how control activity is assembled to meet task demands. Understanding workload therefore involves understanding the strategies that ATCos use to meet task demands. Research in this area focuses on identifying cognitive tasks, eliciting controller strategies, and attempting to build computational models of ATCo activity. In the next section we provide a brief review of human performance models in ATC and note how ATCos manage time pressure. We focus on three main control tasks identified in cognitive task analyses: the higher level control task of maintaining situation awareness and the control subtasks of detecting conflicts and resolving conflicts (Kallus, Van Damme, & Dittman, 1999; Neal et al., 1998; Rodgers & Drechsler, 1993). Research that has examined ATCo strategies is summarized in Table 2.

Human Performance Models

Several models of ATCo performance have been developed over the past decade (Callantine, 2002; Kallus, Van Damme, & Barbarino, 1999; Leiden et al., 2003; Niessen et al., 1999). In general, these models identify the control tasks that ATCos perform, the order in which they carry them out, and the time required and time available to do so. Such models offer insight into sources of mental workload.

Some human performance models are fairly high level, providing a verbal description of behavior (Kallus, Van Damme, & Barbarino, 1999). Others are based on formal architectures such as Adaptive Control of Thought-Rational (Anderson, 1993) and have been validated with empirical data (Leiden et al., 2003; Niessen et al., 1999). For example, the human performance model developed by Leiden et al. (2003) specifically focuses on arrivals streams. Leiden et al. (2003) modeled mental workload using the concepts of "task utilization" and "idle utilization." They identified ATCo tasks, obtained estimates for how long each task took to perform, and predicted how much time sets of tasks would take under different levels of traffic load. Task utilization, therefore, reflects the time required to accept aircraft, resolve conflicts, provide metering, issue descent clearances, handoff aircraft, and transfer communications. Idle utilization is all remaining time. Leiden et al. (2003) used idle utilization as an indicator of available capacity. To our knowledge, however, no studies have directly compared the validity of workload predictions generated by such human performance models with that of predictions generated by dynamic density metrics. A further difficulty with the Leiden et al. (2003) approach is

TABLE 2: Summary of Empirical Studies Examining ATCo Strategy for Control Tasks

Authors	Control Tasks	Method	Summary Results
Amaldi & Leroux (1995)	Maintain SA Conflict detection Conflict resolution	Interview	Group A/C into streams of traffic, selectively extract A/C data for conflict detection (altitude first); attend to critical points where conflicts have previously occurred; decision to intervene or not, and timing, depends on judgment of conflict risk.
Bisseret (1971)	Maintain SA Conflict detection	Interview Experiment	Regulate attention allocated to individual A/C (based on conflict status); selectively extract A/C data for conflict detection (altitude first).
Boudes et al. (1997)	Conflict detection	Interview	Selectively extract aircraft A/C data for conflict detection.
Gronlund et al. (1998)	Maintain SA Conflict detection	Experiment	Selectively attend to A/C (based on spatial position); selectively extract A/C data for conflict detection (altitude first).
Histon & Hansman (2002)	Maintain SA Conflict detection Conflict resolution	Interview Experiment	Classify A/C into standard and nonstandard flows; selectively extract A/C data for conflict detection (altitude first); attend critical points where conflicts have previously occurred.
Kallus, Van Damme, & Dittman (1999)	Conflict detection Conflict resolution	Interview	Attend critical points where conflicts have previously occurred; refer to previously used conflict resolution strategies; under high workload resolve conflicts immediately (make safety first priority).
Kirwan & Flynn (2002)	Conflict resolution	Interview	ATCo uses heuristics for resolving conflicts that minimize control activity.
Leplat & Bisseret (1966)	Conflict detection	Experiment	Selectively extract A/C data for conflict detection (altitude first).
Means et al. (1988)	Maintain SA	Experiment	Regulate attention allocated to individual A/C (based on amount of control previously exercised on A/C).
Neal et al. (1998)	Conflict detection Conflict resolution	Interview	Attend critical points where conflicts have previously occurred; refer to previously used conflict resolution strategies.
Pawlak et al. (1996)	Maintain SA	Interview	Group A/C into streams of traffic.
Redding et al. (1991)	Maintain SA	Interview	Group A/C into streams of traffic.
Rantanen & Nunes (2005)	Conflict detection	Experiment	Selectively extract A/C data for conflict detection (altitude first, heading second, speed third).
Roske-Hofstrand & Murphy (1998)	Maintain SA Conflict detection	Interview	Group A/C into streams of traffic; selectively extract A/C data for conflict detection (altitude first).
Seamster et al. (1993)	Conflict detection Conflict resolution	Interview	Classify A/C into standard and nonstandard flows; attend critical points where conflicts have previously occurred; refer to previously used conflict strategies.
Sperandio (1971)	Maintain SA	Experiment	Regulate attention allocated to individual A/C; group A/C into streams of traffic.
Sperandio (1978)	Maintain SA	Experiment	Regulate attention allocated to individual A/C; group A/C into streams of traffic.
Weitzman (1993)	Conflict resolution	Interview	Choice of conflict detection strategy depends on temporal proximity of the conflict, the geometry of the conflict, and the certainty of the conflict.
Willems et al. (1999)	Conflict detection	Experiment	Regulate attention allocated to individual A/C; selectively extract A/C data for conflict detection (altitude first).

Note. A/C = aircraft; SA = situational awareness.

that it does not estimate the time that ATCos spend building and maintaining situation awareness. Such cognitive activity contributes to workload, but it is unobservable.

Using a human performance model similar to that of Leiden et al. (2003), Callantine (2002) emulated ATCo cognitive activity with a simple set of heuristics for planning and decision making. At the beginning of a processing cycle, the Callantine (2002) model scans the environment to detect tasks that need to be carried out. This is referred to as "maintain situation awareness." The model then selects the task with the highest priority and carries it out. Possible tasks include carrying out a plan that has been developed previously, developing a plan to resolve a conflict, and issuing a descent clearance. A set of rules describes how each of these tasks is carried out. A preliminary evaluation of the Callantine (2002) model demonstrated that it could handle relatively simple spacing problems in high-altitude sectors but performed less well when handling merging traffic in low-altitude sectors. Nonetheless, the results are encouraging because they show that a simple model can control traffic in a plausible manner. The next step is to operationalize the concept of mental workload within this type of model, but that step has yet to be taken.

Time Pressure

Cognitive task analyses demonstrate that ATCos are required to complete many tasks, many of which must be time-shared (e.g., Cox, 1994; Rodgers & Drechsler, 1993). According to an information-processing model developed by Hendy et al. (1997), subjective estimates of mental workload are driven by the ratio of (a) the time needed to process the information necessary to make a decision to (b) the time available before the decision has to be put into action. The most important human constraint, then, is the maximum rate at which work can be done. The competent ATCo generally knows the rate at which he or she can complete tasks, and this knowledge is actively managed by the ATCo to avoid overload. ATCos maintain acceptable levels of workload under heavy task demand by seeking control strategies that minimize the amount of control activity (e.g., planning, monitoring, coordinating) required to meet their objectives and, if necessary, reordering work priorities. According to Hendy et al.'s (1997) model, these changes help to reduce the amount of information that has to be processed. In the next sections we examine how ATCos manage the mental workload associated with maintaining situational awareness.

Maintaining Situational Awareness

ATCos work to maintain a valid mental representation of the current air traffic situation, which is commonly referred to as *situational awareness* (SA; Endsley, 1995; Endsley & Smolensky, 1998). As Dailey (1984) stated, "The central skill of the controller seems to be the ability to respond to a variety of quantitative inputs about several aircraft simultaneously and to form a continuously changing mental picture to be used as the basis for planning and controlling the courses of the aircraft" (p. 134).

SA is usually understood to involve (a) the continuous perception of information in the environment, (b) the integration of this information with prior knowledge to form a coherent understanding or "mental picture" of the current situation, and (c) the use of this mental picture to direct visual search, guide perception, anticipate the future state of air traffic, and plan required actions (Endsley, 1995).

SA is maintained through monitoring, which is the continuous or intermittent comparison of an anticipated versus an actual traffic situation. Monitoring involves directing attention to external sources of information (e.g., sector maps, a radar screen, or flight plans) in order to determine if trajectories of future aircraft movement and positions are consistent with the mental picture. As long as the mental picture remains consistent with actual events, SA is maintained. Research indicates that many operational errors can be attributed to SA problems (e.g., Jones & Endsley, 1996) and, conversely, that scores on measures of SA can predict performance (e.g., Durso, Hackworth, Truitt, Crutchfield, Nikolic, & Manning, 1998). Under heavy task demand ATCos can be so busy dealing with traffic events that they do not have time to update their mental picture, cannot plan ahead, and are forced to work reactively. ATCos refer to this as "losing the picture." However, as will be discussed shortly, ATCos have strategies that help avoid this situation.

To assess ATCo SA, query techniques are commonly used that tap ATCos' ability to recall information about the air traffic situation (Adams, Tenney, & Pew, 1995). Findings suggest that ATCos can reduce the mental workload associated with monitoring by regulating the amount of attention they give to individual aircraft (Bisseret, 1971; Gronlund et al., 1998; Sperandio, 1971). Early studies indicated that ATCos could recall more about the positions and flight data of aircraft on which they had performed control actions (Means et al., 1988) or of aircraft that were in potential conflict (Bisseret, 1971; Sperandio, 1971), as compared with aircraft on which they had not performed control actions or which were not in potential conflict. More recently, Gronlund et al. (1998) found that ATCos appeared to classify aircraft into two categories – important versus nonimportant – on the basis of how soon they would lose separation with other aircraft. Although there was no difference in ATCos' ability to recall the two-dimensional position or heading of important versus nonimportant aircraft, ATCos were more likely to recall the altitude and ground speed of important aircraft. Gronlund et al. (1998) concluded that ATCos assigned importance to aircraft on the basis of relative spatial position to other aircraft, and that information not presented spatially (e.g., altitude, speed) was selectively attended on the basis of this importance weighting.

As noted previously, the underlying structure of the airspace can become the basis for abstractions that simplify the ATCo's cognitive work (Histon & Hansman, 2002; Seamster, Redding, Cannon, Ryder, & Purcell, 1993). Field observations conducted by Histon and Hansman (2002) indicated that *standard flows* are one of the most important structure-based abstractions. ATCos classify aircraft into standard and nonstandard classes according to their match with standard flow, which would include the aircraft's future routing, ingress and engress points, coordination requirements, and crossing routes/altitude profiles (Histon & Hansman, 2002; Seamster et al., 1993). These factors allow the ATCo to form a general expectation of how aircraft will move through the sector, significantly reducing the complexity of control. Aircraft classified as nonstandard increase the complexity of control because their trajectory and interactions with other aircraft are more difficult to predict a priori.

In addition, structured interviews reveal that ATCos process aircraft in groups to reduce the information-processing requirements associated with monitoring air traffic (Amaldi & Leroux, 1995; Histon & Hansman, 2002; Redding, Ryder, Seamster, Purcell, & Cannon, 1991). For example, if four aircraft are heading southbound and six aircraft northbound, the ATCo might process and monitor the four southbound aircraft as one stream and the six northbound aircraft as another stream, rather than monitor each individual aircraft. ATCos report that such strategies let them focus on the intersection of the two streams, rather than requiring them to assess the conflict status of each possible aircraft pair (Pawlak et al., 1996). Aircraft separation within streams is maintained by speed control (Sperandio, 1978), and separation between streams at common intersection points is maintained by altitude control. Overall, establishing streams simplifies the process of maintaining SA, letting the ATCo work with more aircraft simultaneously and use fewer control actions.

Conflict Detection

One aspect of SA that is particularly critical is *conflict detection.* Conflict detection research has tended to focus on (a) factors that increase the complexity of detecting conflicts or (b) strategies that ATCos use to minimize this complexity. The connection with mental workload is seldom explicitly addressed, although increases in the time taken to detect conflicts have been associated with greater mental workload ratings (e.g., Galster, Duley, Masalonis, & Parasuraman, 2001; Metzger & Parasuraman, 2001). In an operational context, a delay in conflict detection imposes constraints on the ATCo because it decreases the time available to intervene and ensure separation. A reduced time to implement a conflict resolution plan can force an ATCo into a situation in which he or she has to create a disorderly flow of traffic, which has the potential to cause problems in the future (Cox, 1994; Kallus, Van Damme, & Dittman, 1999). In contextual control terms (e.g., Hollnagel, 2002), this could represent one aspect of the shift from tactical to a reactive control.

Several studies have examined how task demand affects the accuracy and timeliness of conflict detection (Boag et al., 2006; Galster et al., 2001; Leplat & Bisseret, 1966; Metzger & Parasuraman, 2001; Nunes & Scholl, 2004; Rantanen & Nunes, 2005; Remington, Johnston, Ruthruff, Gold, & Romera, 2000). For example, Remington et al. (2000) found that conflict detection accuracy decreased, and conflict detection latency increased, with higher traffic count and increasing angles of convergence. Conflict detection latency also increased as time to conflict increased. Higher traffic count presumably affects conflict detection by increasing visual search requirements and reducing the time available to make conflict status decisions (Hendy et al. 1997). Boag et al. (2006) showed that the number of aircraft transitions in and out of conflict positively predicted detection time. Similarly, Leplat and Bisseret (1966) found that ATCos took longer to detect conflicts when three variables needed to be processed to determine conflict status (e.g., altitude, heading, and speed) than when only one variable needed to be processed.

Nevertheless, ATCos may change their strategy for conflict detection in response to these task demands and anticipated mental workload. For example, ATCos appear to prefer using altitude information to heading and speed information when determining the likelihood of aircraft conflict (Amaldi & Leroux, 1995; Leplat & Bisseret, 1966; Willems, Allen, & Stein, 1999). This finding is supported by cognitive task analyses (Kallus, Van Damme, & Dittman, 1999; Neal et al., 1998; Seamster et al., 1993), interviews with controllers (Amaldi & Leroux, 1995; Boudes, Amaldi, & Cellier, 1997), anecdotal reports (Roske-Hofstrand & Murphy, 1998; Wickens, Mavor, & McGee, 1997), and experiments (Bisseret, 1971; Gronlund et al., 1998; Rantanen & Nunes, 2005). Taken together, this body of research suggests that ATCos save attentional resources by extrapolating aircraft trajectories for lateral separation only in circumstances where vertical separation is questionable. Furthermore, ATCos prefer to use altitude and heading information over speed information (Bisseret, 1971; Leplat & Bisseret, 1966; Rantanen & Nunes, 2005; Willems et al., 1999). Presumably, this is attributable to the greater cognitive effort associated with processing speed information (see Law et al., 1993).

A further strategy that ATCos use to detect conflicts, already touched upon, is to exploit airspace structure and standard flows (Amaldi & Leroux, 1995; Histon & Hansman, 2002; Kallus, Van Damme, & Dittman, 1999; Neal et al., 1998; Roske-Hofstrand & Murphy, 1998; Seamster et al., 1993). Specific aircraft events occur routinely at specific locations in a sector, and ATCos learn to recognize specific air traffic configurations. Memory for past experiences lets ATCos anticipate where conflicts may occur (sector “hot spots” or “critical points”), simplifying the cognitive work of detecting conflicts. By focusing on a finite number of critical crossing points, ATCos do not need to evaluate the likelihood of conflict between all aircraft pairs in the sector, thus reducing task demands and, presumably, mental workload.

Conflict Resolution

The ATC literature has provided some useful insights into the strategies that ATCos use to resolve conflicts under different levels of task demand and thus regulate their mental workload. On the basis of detailed interviews with ATCos, several research groups have argued that the workload associated with resolving conflicts depends largely on sector-specific knowledge that ATCos acquire over time (Kallus, Van Damme, & Dittman, 1999; Neal et al., 1998; Seamster et al., 1993). ATCos often report that they have the equivalent of a “conflict resolution library” of solutions to particular configurations of air traffic (Kallus, Van Damme, & Dittman, 1999). When a conflict is detected, ATCos “access” their library to find a previous solution and then adapt and apply that previous solution to the new case. If no appropriate solution is found, ATCos must either review their solution library for a suitable plan or use problem-solving techniques to develop a new solution. Retrieving a solution from memory reduces cognitive work and the associated workload.

ATCos also regulate mental workload by being selective about when they intervene to ensure separation. ATCos interviewed by Kallus, Van Damme, and Dittman (1999) reported that under low workload they tend not to solve conflicts immediately because it can reduce the efficiency of aircraft movement. They prefer to monitor the situation. Under high-workload conditions, however, they are reluctant to let potential conflicts run unless intervening tasks leave them with enough capacity to monitor the potential conflict. Under high workload they tend to solve problems by taking immediate action in order to conserve attentional resources. This strategy also reduces the likelihood that they will forget to return to the unresolved situation because of distraction from competing tasks (Loft, Humphreys, & Neal, 2003).

Interviews with ATCos conducted by Amaldi and Leroux (1995; also see Weitzman, 1993) indicate that a further factor determining when ATCos intervene is their judgment of the probability that the aircraft pair will violate separation. If they respond to every possible conflict they are proactive but overloaded, whereas if they respond only to definite conflicts they are reactive and may lose the picture. Under high mental workload conditions ATCos shift their criterion for classifying conflicts, becoming more conservative so that they intervene to ensure separation if there is any uncertainty regarding future separation between aircraft. Although such a change in conflict detection criterion may temporarily increase ATCo control activity, it will significantly reduce the amount of control activity required in the longer term. Moreover, when intervening to ensure separation under conditions of high workload, ATCos choose solutions that require minimum monitoring and coordination. In this way, ATCos maintain resilient control. For example, Kirwan and Flynn (2002) identified various heuristics ATCos use to resolve conflicts, such as (a) using as few control actions as possible, (b) giving aircraft initial level changes early and fine-tuning later, (c) using solutions that require less coordination, (d) using vertical separation for complex conflicts, and (e) keeping solutions simple and safe.

Summary and Assessment

The key characteristic of the ATCo mental workload model presented in Figure 3 is that the ATCos do not passively react to events but, instead, actively control workload by selecting strategies that have different demands on cognitive resources. Operator capacity is therefore not a static property of the ATCo but a dynamic one. In this section we reviewed efforts to identify the control tasks that ATCos perform and the strategies ATCos use to minimize the control activity associated with these control tasks, in order to understand workload.

Human performance models have been developed that integrate ATCo control tasks into computational frameworks, but such models generally do not include sophisticated sets of strategies, model mental workload, or demonstrate how mental workload might drive the selection of strategies. Research on time pressure suggests that one way workload might be modeled is as a function of the ratio of the time to perform a task to the time available before the task must be completed. Task timing information for specific control tasks could be estimated via empirical data (e.g., Cardosi, 1993), interviews (e.g., Amaldi & Leroux, 1995), cognitive task analyses (e.g., Kallus, Van Damme, & Dittman, 1999) or observation (e.g., Histon & Hansman, 2002). If mappings between workload – however it is measured – and selection of strategies could be operationalized within human performance models, a better understanding could probably be gained of the adaptive nature of ATCo work and of workload itself.

Research on three principal ATCo activities – maintaining SA, detecting conflicts, and resolving conflicts – provides abundant evidence that ATCos seek ways of minimizing mental workload. The workload of maintaining SA can be reduced by using standard flows and by grouping aircraft so that many aircraft can be handled in one operation. Moreover, by focusing on altitude information and seeking resolution on that basis before considering heading and speed, ATCos seek to reduce workload. The workload associated with the subtask of conflict detection is also amenable to strategic control. For example, sector structure produces locations where conflicts are more likely or less likely. The workload of resolving conflicts can be reduced through development and use of a repertoire of solutions mapped to the imminence, probability, and geometry of potential conflicts, as well as the timing of interventions. Overall, ATCos attend to cues that give them the smallest amount of information necessary for effective decision making according to the priorities chosen for performance.

All the these factors can in principle be modeled computationally, leading to a better understanding of the relation among task demands, ATCo activity, and ATCo mental workload, but operationalization can be difficult. In the next section we review models that reflect such modeling.

MODELS INTEGRATING TASK DEMANDS WITH OPERATOR ACTIVITY

This review has focused on two broad determinants of mental workload: task demands (the amount and complexity of work) and operator capacity (the resources the ATCo can marshal to meet demand, including strategies). There have been some relatively recent efforts by researchers to develop techniques that integrate task demand with operator capacity in order to predict workload (Averty, Athènes, Collet, & Dittmar, 2002; Averty et al., 2004; Chaboud, Hunter, Hustache, Mahlich, & Tullett, 2000; Cullen, 1999; Stamp, 1992).

For example, Chaboud et al. (2000) developed a model that describes the mental workload corresponding to different control tasks. First, the model describes workload for routine tasks, such as flight data management, coordination, and radio communications. The workload value is based on the number of aircraft sector entries and is multiplied by the estimated time it would take ATCos to complete the task (task duration). Second, a value is assigned for the workload associated with climbing and descending aircraft, defined as the number of aircraft with a 6,000-foot vertical evolution multiplied by task duration. Third, a value is assigned based on the workload associated with monitoring conflicts, defined as the number of conflicts multiplied by task duration. This workload metric correlated well with ATCo activity measures but was not validated with an independent workload measure. Two significant limitations of the work of Chaboud et al. (2000) are that (a) the workload weights assigned to different control tasks were fixed and (b) the durations assigned to tasks were fixed. These methods do not take into account the fact that the workload associated with different control tasks can be modulated by the use of strategy.

Averty et al. (2002, 2004) developed a metric called the traffic load index (TLI), which takes into account the fact that, through their actions, ATCos will regulate their own mental workload. The TLI is calculated by assigning each aircraft under jurisdiction a weight that contributes toward the TLI for the sector. Aircraft under jurisdiction of the ATCo are assigned a base weight of 1. Any aircraft that need additional monitoring – for example, because they are anticipated to be involved in a conflict or will need vectoring on their descent profile into an airport – accrue additional weighting. The weighting is thus a measure of the amount of monitoring each aircraft requires. This first part of the TLI provides a simple measure of task demand. The second part of the TLI assesses the effects of ATCo activity. If the ATCo sees a potential conflict but waits a long time before resolving it, then the so-called maturing time (MT) before acting is protracted and workload associated with monitoring is increased. In contrast, if the ATCo resolves the potential conflict immediately, MT is short and monitoring workload is removed. Even if action is taken immediately, in some cases separation may not be ensured for quite a long time, leading to a long MT because of the remaining uncertainty. Acting earlier removes time pressure to act but leaves some uncertainty as to whether a conflict will be resolved as desired. In contrast, acting later imposes time pressure when one does come to act, but it provides greater certainty as to whether the conflict will be resolved as desired.

Averty et al. (2002, 2004) have shown that the correlation between the NASA Task Load Index (NASA-TLX; Hart & Staveland, 1988) and TLI was significantly higher than that between the traffic count and NASA-TLX. This indicates that TLI is a better predictor of ratings of mental workload than is traffic count. In addition, the TLI had higher correlations with all physiological workload measures than did both traffic count and the NASA-TLX. By modeling the timing of ATCos' interventions, the TLI measure goes some way in capturing the effect of different ATCo strategies on workload.

In a further effort, Cullen (1999) built a mental workload model in which she attempted to quantify the sequences and durations of ATCo tasks. Factors influencing the sequence and durations of tasks included (a) environmental conditions that initiated each task, (b) priorities assigned to tasks (urgent, high, low), (c) rules specifying which tasks could be interrupted by tasks of higher priority, and (d) rules governing task selection and sequence. The task model soundly predicted task durations. However, the model's ability to predict task sequence and workload was poor. In general, observed workload was higher than predicted workload. Cullen (1999) concluded that workload was poorly predicted because the task model could not accurately predict sequences of ATCo activity. A closer inspection of the model indicates that it did not take into account the effects of workload management strategies on the sequences and durations of task behavior. In addition, the model did not account for the fact that multiple tasks are often completed concurrently or that ATCos often monitor the progress of aircraft after issuing instructions to ensure pilot compliance and adequate separation. Overall, the predictive validity of Cullen's (1999) model was disappointing. Notably, the factors missing from the model included factors modeled in Figures 2 and 3 and discussed in preceding sections of this review.

A further and very important model that integrates task demands with operator activity is the Man-Machine Interaction Design and Analysis System (MIDAS; Corker & Smith, 1993). MIDAS is not a mental workload model per se but a human performance model used for the analysis of human-machine systems design issues. MIDAS is a first-principles model of human performance, built upon 35 primitive operator tasks such as visual monitoring, typing, grasping, and computing. Each of these tasks is assigned a workload weight on each of the six channels from multiple resource theory (Wickens, 1984): visual and auditory input, spatial and verbal cognitive processing, and manual and voice output. Additionally, MIDAS has a dynamic mechanism for switching between control strategies that is based on Hollnagel's (2002) COCOM model. The model switches among strategic, tactical, opportunistic, and scrambled control depending on four control parameters: the event horizon (a measure of success of previous control actions taken by the operator), an estimate of the time available for the control activity, an estimate of the time required to complete the control activity, and an estimate of competency (measured in the number of goals). The specific values of these control variables that will make MIDAS switch between different control strategies are domain dependent. For the ATCo model in Air MIDAS, the aviation-specific version of MIDAS, the event horizon is measured in number of aircraft under control and the complexity of maneuvers the aircraft have to perform (Corker, 2003). Evaluations of Air MIDAS have been performed, but detailed reports are still forthcoming.

SUMMARY AND CONCLUSION

The most prevalent approach to studying the mental workload of ATCos is to investigate traffic factors that produce or influence task demand, on the assumption that there is a relationship between task demand and mental workload that is mediated by control strategy (see Figure 1). In this paper we reviewed this and other modeling architectures that have been used to understand workload in ATC. Influenced by Sperandio's (1971) emphasis on the central role of alternative work methods, or strategies, in controlling workload (Figure 2), we developed a model expanding on the ATCo's role in selecting an appropriate strategy for meeting task demands (Figure 3). The model shows strategy being driven on a proactive/feedforward basis as well as on a reactive/feedback basis. The model also shows strategy being driven not only by task demands but also by judgments about work priorities that is, by a hierarchy of standards that ATCos aim to preserve.

In the body of this review, we organized the vast literature on ATCo performance around two major themes: research investigating the relationship between task demands and mental workload, and research investigating the relationship between ATCo capacity and mental workload. Much of the latter work emphasizes the crucial role of ATCo strategies in handling task demand. Toward the end of the review we examined models in which researchers have attempted to integrate these two themes. The overall impression is that there is still a long way to go before ATCo workload is fully understood, let alone modeled computationally to a level that would support robust organizational decision making about allocation of ATCo work through sector sizes, rostering, and so on.

Much research still seeks relationships between task demands and ATCo mental workload in the open-loop manner illustrated in Figure 1. However, simply "integrating" task demand and operator capacity in closed-loop models is unlikely to help in modeling workload. Information is also needed about strategies, performance priorities, and an appropriate architecture to link all these elements. Figure 3 represents an attempt to do so. This approach may be more useful in understanding ATCo workload than attempting to model the relationship between isolated traffic factors and ATCo speed or accuracy of responding. However, an even more appropriate architecture may be one that models – far more explicitly even than that in Figure 3 – the fact that ATCos regulate their workload by selecting control strategies that meet task demands, driven by the relative priority of their objectives. Figure 4 shows the simplest form of such a workload regulation model. In Figure 4, a deviation from the desired level of workload leads to an adjustment of control strategy, and the control strategy shapes the task demands that produce actual workload. Actual workload is compared with the desired level of workload, and the loop repeats.

One strength of the mental workload models presented in Figures 3 and 4 is that they use relatively domain-independent system-level parameters (e.g., task demand, metacognition, prioritization, strategy). Consequently, as outlined in the introduction to this paper, operational models of workload could be developed for a variety of complex work systems (e.g., piloting, unmanned aerial vehicle control, anesthesiology, railway signaling, and automobile driving) using the conceptual models presented in Figures 3 and 4.

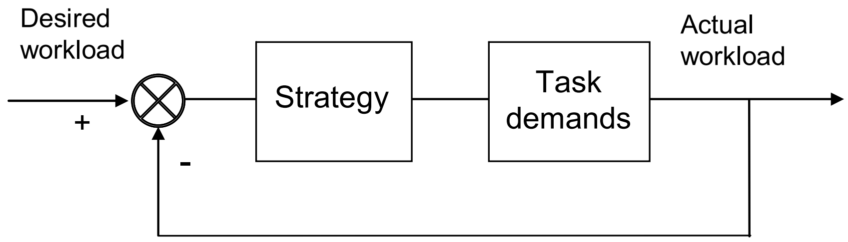

Figure 4. Model of the regulation of mental workload by adapting strategy to task demands.

Moreover, it suggests quite a different way of investigating workload in complex work systems. First, instead of investigating the linear relationship between task demand and workload at specific moments in time, one might investigate dynamic properties of workload that could show workload to lead or lag events (Rouse et al., 1993). Second, one might investigate workload signals, rather than task demand signals, that lead to a switch in strategy. Third, one might investigate how operators learn signals relevant for managing workload and developing essential skills (e.g., estimating time needed to execute plans, estimating when events will occur), and examine the relationship between the two. Fourth, one might investigate far more thoroughly than before how strategies create specific patterns of task demands. Fifth, one might study the impact of operators' persistence with inappropriate strategies on both workload and control quality and how any such problems might be alleviated. This list is not exhaustive – there are many further possible implications of taking such an approach to conceptualizing both ATCo workload and workload in other complex work systems.

Finally, taking a mental workload-centered view rather than a task demand-centered view may have longer term benefits. Globally, this is an era of rapid changes in air traffic management (EUROCONTROL, 1999; Federal Aviation Administration, 2005). For example, "free flight" refers to a wide variety of ATC regimens that all share the following characteristics: an increase in airspace capacity through new decision support tools, increased automation to aid the ATCo, and increased flexibility for airline and aircraft operations. Similarly, in modern aircraft, pilots are provided with host of automated flight control systems that automate tasks such as status monitoring and flight mode (e.g., climb, cruise descend; Kantowitz, 1994; Wickens, 2002). Aviation providers and regulatory bodies need tools that are capable of assessing the workload experienced by operators under these proposed systems. Models that focus primarily on the link between task demand and workload are likely to have difficulty generalizing to new automation systems because operator control strategies will change. More fully developed models that show how control strategies regulate task demand and thereby workload would be extremely useful because they would let researchers explore the consequences of new control arrangements. Good progress has been made in describing the empirical relationship between task demand and workload in many complex work systems. The next step is to develop and test dynamic models that explain the relationship among workload, task demands, and strategy-driven activity within current and future systems.

ACKNOWLEDGMENTS

This research was supported by Linkage Grant LP0453978 from the Australian Research Council and Airservices Australia and a postdoctoral research fellowship awarded to Shayne Loft from the Australian Research Council.

REFERENCES

Adams, M. J., Tenney, Y. J., & Pew, R. W. (1995). Situational awareness and the cognitive management of complex systems. *Human Factors, 37,* 85–104.

Amaldi, P., & Leroux, M. (1995). Selecting relevant information in a complex environment: The case of air traffic control. In L. Norros (Ed.), *5th European Conference on Cognitive Science Approaches in Process Control* (pp. 89–98). Espoo, Finland: VTT Automation.

Anderson, J. R. (1993). *Rules of the mind.* Hillsdale, NJ: Erlbaum.

Arad, B. A. (1964, May). The controller load and sector design. *Journal of Air Traffic Control,* 12–31.

Athènes, S., Averty, P., Puechmorel, S., Delahaye, D., & Collet, C. (2002). Complexity and controller workload: Trying to bridge the gap. In *Proceedings of the 2002 International Conference on Human-Computer Interaction in Aeronautics* (pp. 56–60). Cambridge: Massachusetts Institute of Technology.

Averty, P., Athènes, S., Collet, C., & Dittmar, A. (2002, October). *Evaluating a new index of mental workload in real ATC situation using psychophysiological measures.* Paper presented at the 21st Digital Avionics System Conference, Irvine, CA.

Averty, P., Collet, C., Dittmar, A., Vernet-Maury, E., & Athènes, S. (2004). Mental workload in air traffic control: An index constructed from field tests. *Aviation, Space, and Environmental Medicine, 75,* 333–341.

Bisseret, A. (1971). An analysis of mental model processes involved in air traffic control. *Ergonomics, 14,* 565–570.

Boag, C., Neal, A., Loft, S., & Halford, G. (2006). An analysis of relational complexity in an air traffic control conflict detection task. *Ergonomics, 49,* 1508–1526.

Boudes, N., Amaldi, P., & Cellier, J. M. (1997). Memory performance and diagnostic processes in air traffic control. In S. Bagnara, E. Hollnagel, M. Mariani, & L. Norros (Eds.), *Time and space in process control: Proceedings of the 6th European Conference on Cognitive Science Approaches to Process Control* (pp. 204–208). Espoo, Finland: VTT Automation.

Buckley, E. P., DeBaryshe, B. D., Hitchner, N., & Kohn, P. (1983). *Methods and measurements in real time air traffic control system simulation* (Rep. No. DOT/FAA/CT-83/26). Washington, DC: U.S. Department of Transportation, Federal Aviation Administration.

Callantine, T. J. (2002). *CATS-based air traffic controller agents* (Rep. No. NASA/CR-2002-211856). Moffett Field, CA: NASA Ames Research Center.

Cardosi, K. M. (1993). Time required for transmissions of time-critical air traffic control messages in an en route environment. *International Journal of Aviation Psychology, 3,* 303–313.

Chaboud, T., Hunter, R., Hustache, J. C., Mahlich, S., & Tullett, P. (2000). *Investigating air traffic complexity: Potential impacts on workload and costs* (European Experimental Centre Note No. 11/00). Brussels, Belgium: EUROCONTROL.

Chatterji, G. B., & Sridhar, B. (2001). Measures for air traffic controller workload prediction. In *Proceedings of the 1st AIAA Aircraft, Technology, Integration, and Operations Forum* [CD-ROM]. Reston, VA: American Institute of Aeronautics and Astronautics.

Christien, R., Benkouar, A., Chaboud, T., & Loubieres, P. (2003, June). *Air traffic complexity indicators and ATC sectors classification.* Paper presented at the 5th USA/Europe Air Traffic Management R & D Seminar, Budapest, Hungary.

Corker, K. M. (2003). A cognitive framework for operation of advanced aerospace technologies. In E. Hollnagel (Ed.), *Handbook of cognitive task design.* (pp. 417–446). Mahwah, NJ: Erlbaum.

Corker, K. M., & Smith, B. R. (1993, September). *An architecture and model for cognitive engineering simulation analysis: Application to advanced aviation automation.* Paper presented at the AIAA Computing in Aerospace 9 Conference, San Diego, CA.

Couluris, G. J., & Schmidt, D. K. (1973). *Air traffic control jurisdictions of responsibility and airspace structure.* Paper presented at the 1973 Institute of Electrical and Electronics Engineers (IEEE) Conference on Decision and Control held December 5–7 in San Diego, CA.

Cox, M. (1994). *Task analysis of selected operating positions within UK air traffic control* (IAM Rep. No. 769). Farnborough, UK: Royal Air Force Institute for Aviation Medicine.

Cullen, L. (1999). *Validation of a methodology for predicting performance and workload* (European Experimental Centre Note No. 7/99). Brussels, Belgium: EUROCONTROL.

Dailey, J. T. (1984). Characteristics of the air traffic controller. In S. B. Sells, J. T. Dailey, & E. W. Pickerel (Eds.), *Selection of air traffic controllers* (No. FAA-AM-84-2; pp. 128–141). Washington, DC: Federal Aviation Administration Office of Aviation Medicine.

Davis, C. G., Danaher, J. W., & Fischl, M. A. (1963). *The influence of selected sector characteristics upon ARTCC controller activities* (Contract No. FAA/BRD-301). Arlington, VA: Matrix.

Dixon, S. R., Wickens, C. D., & Chang, D. (2005). Mission control of multiple unmanned aerial vehicles: A workload analysis. *Human Factors, 47,* 479–488.

Durso, F. T., Hackworth, C. A., Truitt, T. R., Crutchfield, J. M., Nikolic, D., & Manning, C. A. (1998). Situation awareness as a predictor of performance for en route air traffic controllers. *Air Traffic Control Quarterly*, *6,* 1–20.

Endsley, M. R. (1995). Toward a theory of situational awareness in dynamic systems. *Human Factors, 37,* 32–64.

Endsley, M. R., & Smolensky, M. W. (1998). Situational awareness in air traffic control: The picture. In M. W. Smolensky & E. S. Stein (Eds.), *Human factors in air traffic control* (pp. 115–154). San Diego, CA: Academic Press.

European Organisation for the Safety of Air Navigation (EUROCONTROL). (1999). *Operational concept document of the strategy 2000+*. Brussels, Belgium: Author.

Farmer, E., & Brownson, Q. (2003). *Review of workload measurement, analysis and interpretation methods* (European Air Traffic Management Programme Rep. No. CARE-Integra-TRS-130-02-WP2). Brussels, Belgium: EUROCONTROL.

Federal Aviation Administration. (2005). *Flight plan 2005–2009.* Washington, DC: Author.

Galster, S. M., Duley, J. A., Masalonis, A. J., & Parasuraman, R. (2001). Air traffic controller performance and workload under mature free flight: Conflict detection and resolution of aircraft self-separation. *International Journal of Aviation Psychology, 11,* 71–93.

Gopher, D., & Donchin, E. (1986). Workload: An examination of the concept. In K. R. Boff, L. Kaufman, & J. P. Thomas (Eds.), *Handbook of perception and performance: Volume 2. Cognitive processes and performance* (pp. 41–49). New York: Wiley.

Griffin, M. A., Neal, A., & Neale, M. (2000). The contribution of task performance and contextual performance to effectiveness in air traffic control: Investigating the role of situational constraints. *Applied Psychology: An International Review, 49,* 517–533.

Gronlund, S. D., Ohrt, D. D., Dougherty, M. R. P., Perry, J. L., & Manning, C. A. (1998). Role of memory in air traffic control. *Journal of Experimental Psychology: Applied, 4,* 263–280.

Grossberg, M. (1989). *Relation of sector complexity to operational errors* (Quarterly Rep. of the FAA Office of Air Traffic Evaluations and Analysis). Washington, DC: Federal Aviation Administration.

Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. In P. A. Hancock & N. Meshkati (Eds.), *Human mental workload: Advances in psychology* (Vol. 52, pp. 139–183). Oxford, UK: North Holland.

Hart, S. G., & Wickens, C. D. (1990). Workload assessment and prediction. In H. R. Booher (Ed.), *MANPRINT: An emerging technology. Advanced concepts for integrating people, machine, and organizations* (pp. 257–296). New York: Van Nostrand Reinhold.

Hendy, K. C., Liao, J., & Milgram, P. (1997). Combining time and intensity effects in assessing operator information-processing load. *Human Factors, 39,* 30–47.

Hilburn, B. (2004). *Cognitive complexity in air traffic control: A literature review* (EUROCONTROL Experimental Centre Note No. 04/04). Brussels, Belgium: EUROCONTROL.

Hilburn, B., & Jorna, P. G. A. M. (2001). Workload and air traffic control. In P. A. Hancock & P. A. Desmond (Eds.), *Stress, workload, and fatigue: Human factors in transportation* (pp. 384–394). Mahwah, NJ: Erlbaum.

Histon, J. M., & Hansman, R. J. (2002). *The impact of structure on cognitive complexity in air traffic control* (Rep. No. ICAT-2002-4). Cambridge, MA: MIT International Center for Air Transportation.

Hollnagel, E. (2002). Time and time again. *Theoretical Issues in Ergonomic Science, 3,* 143–158.

Hollnagel, E., & Woods, D. D. (2005). *Joint cognitive systems: Foundations of cognitive systems engineering.* Boca Raton, FL: CRC Press.

Hopkin, V. D. (1995). *Human factors in air traffic control.* London: Taylor & Francis.

Hurst, M. W., & Rose, R. M. (1978). Objective job difficulty, behavioral response, and sector characteristics in air route traffic control centers. *Ergonomics, 21,* 697–708.

International Civil Aviation Organization. (2004). *Outlook for air transport to the year 2015* (Circular 304). Montreal, Canada: Author.

Jones, D. G., & Endsley, M. R. (1996). Sources of situational awareness errors in aviation. *Aviation, Space, and Environmental Medicine, 67,* 507–512.

Kallus, K. W., Van Damme, D., & Barbarino, M. (1999). *Model of the cognitive aspects of air traffic control* (European Air Traffic Management Programme Rep. No. HUM.ET1.ST01.1000-REP-04). Brussels, Belgium: EUROCONTROL.

Kallus, K. W., Van Damme, D., & Dittman, A. (1999). *Integrated job and task analysis of air traffic controllers: Phase 2. Task analysis* *of en-route controllers* (European Air Traffic Management Programme Rep. No. HUM.ET1.ST01.1000-REP-04). Brussels, Belgium: EUROCONTROL.

Kantowitz, B. H. (1994). Pilot workload and flight deck automation. In M. Mouloua & R. Parasuraman (Eds.), *Human performance in automated systems: Current research and trends* (pp. 212–223). Hillsdale, NJ: Erlbaum.

Kirwan, B., & Flynn, M. (2002). *Towards a controller-based conflict resolution tool – A literature review* (European Air Traffic Management Programme Rep. No. ASA.01.CORA.2.DEL04-A.LIT). Brussels, Belgium: EUROCONTROL Experimental Centre.

Kirwan, B., Scaife, R., & Kennedy, R. (2001). Investigating complexity factors in UK air traffic management. *Human Factors and Aerospace Safety, 1*, 125–144.

Kopardekar, P., & Magyarits, S. (2003, June). *Measurement and prediction of dynamic density.* Paper presented at the 5th USA/Europe ATM R & D Seminar, Budapest, Hungary.

Lamoureux, T. (1999). The influence of aircraft proximity data on the subjective mental workload of controllers on the air traffic control task. *Ergonomics, 42,* 1482–1491.

Laudeman, I., Shelden, S., Branstrom, R., & Brasil, C. (1998). *Dynamic density: An air traffic management metric* (NASA-TM-1988-11226). Moffet Field, CA: NASA Ames Research Center.

Law, D. J., Pellegrino, J. W., Mitchell, S. R., Fischer, S. C., McDonald, T. P., & Hunt, E. B. (1993). Perceptual and cognitive factors governing performance in comparative arrival-time judgments. *Journal of Experimental Psychology: Human Perception and Performance, 19,* 1183–1199.

Leedal, J. M., & Smith, A. F. (2005). Methodological approaches to anesthetist's workload in the operating theatre. *British Journal of Anaesthesia, 94,* 702–709.

Leiden, K. J., Kopardekar, P., & Green, S. (2003, November). *Controller workload analysis methodology to predict increases in airspace capacity.* Paper presented at the AIAA's 3rd Annual Aviation Technology, Integration, and Operations (ATIO) Forum, Denver, CO.

Leplat, J., & Bisseret, A. (1966). Analysis of the processes involved in the treatment of information by the air traffic controller. *Controller, 1,* 13–22.

Loft, S., Humphreys, M., & Neal, A. (2003). Prospective memory in air traffic control. In G. Edkins & P. Pfister (Eds.), *Innovation and consolidation in aviation* (pp. 287–293). Aldershot, UK: Ashgate.

Majumdar, A., & Ochieng, W. (2002). Factors affecting air traffic controller workload: A multivariate analysis based upon simulation modeling of controller workload. *Transportation Research Record: Journal of the Transportation Research Board, 1788,* 58–69.

Majumdar, A., Ochieng, W., McAuley, G., Lenzi, J. M., & Lepadatu, C. (2004). The factors affecting airspace capacity in Europe: A cross sectional time-series analysis using simulated controller workload data. *Journal of Navigation, 57,* 385–405.

Manning, C., Mills, S., Fox, C., & Pfleiderer, E. (2001). *Investigating the validity of performance and objective workload evaluation research (POWER)* (Rep. No. DOT/FAA/AM-01/10). Washington, DC: Federal Aviation Administration Office of Aviation Medicine.

Manning, C., Mills, S., Fox, C., Pfleiderer, E., & Mogilka, H. (2002). *Using air traffic control taskload measures and communication events to predict subjective workload* (No. DOT/FAA/AM-02/4). Washington DC: Federal Aviation Administration Office of Aviation Medicine.

Masalonis, A. J., Callaham, M. B., & Wanke, C. R. (2003). *Dynamic density and complexity metrics for realtime traffic flow management.* McLean, VA: MITRE.

Means, B., Mumaw, R. J., Roth, C., Schlager, M. S., McWilliams, E., Gagné, E., et al. (1988). *ATC training analysis study: Design of the next generation ATC training system* (Rep. No. FAA/OPM 342-036). Washington, DC: U.S. Department of Transportation/Federal Aviation Administration.

Metzger, U., & Parasuraman, R. (2001). The role of the air traffic controller in future air traffic management: An empirical study of active control versus passive monitoring. *Human Factors, 43,* 519–528.

Mogford, R. H., Guttman, J., Morrow, S. L., & Kopardekar, P. (1995). *The complexity construct in air traffic control: A review and synthesis of the literature* (No. DOT/FAA/CT-TN95/22). Atlantic City, NJ: Federal Aviation Administration, William Hughes Technical Center.

Mogford, R. H., Murphy, E. D., Yastrop, G., Guttman, J. A., & Roske-Hofstrand, R. J. (1993). *The application of research techniques for documenting cognitive processes in air traffic control* (Rep. No. DOT/FAA/CT-TN93/39). Atlantic City, NJ: Federal Aviation Administration.

Moray, N. (1979). *Mental workload: Its theory and measurement.* New York: Plenum Press.

Moray, N. (1997). Human factors in process control. In G. Salvendy (Ed.), *Handbook of human factors and ergonomics* (pp. 1944–1971). New York: Wiley.

Neal, A., Griffin, M., Neale, M., Bamford, E., & Boag, C. (1998). *Human factors issues in the transition to a CNS/ATM environment: Final report* (Report prepared for AirServices Australia). Brisbane, Australia: University of Queensland.

Niessen, C., Eyferth, K., & Bierwagen, T. (1999). Modeling cognitive processes of experienced air traffic controllers. *Ergonomics, 42,* 1507–1520.

Nunes, A., & Scholl, B. J. (2004). Interactions between convergence angle, traffic load, and altitude distribution in air traffic control. In D. A. Vincenzi, M. Mouloua, & P. A. Hancock (Eds.), *Human performance, situation awareness and automation technology*: *Current research and trends* (pp. 180–185). Mahwah, NJ: Erlbaum.

Pawlak, W. S., Brinton, C. R., Crouch, K., & Lancaster, K. M. (1996, July). *A framework for the evaluation of air traffic control complexity.* Presented at the AIAA Guidance, Navigation and Control Conference, San Diego, CA.

Pickup, L., Wilson, J. R., Sharpies, S., Norris, B., Clarke, T., & Young, M. S. (2005). Fundamental examination of mental workload in the rail industry. *Theoretical Issues in Ergonomics Science, 6,* 463–482.

Rantanen, E., & Levinthal, B. (2005). Time-based modeling of human performance. In *Proceedings of the Human Factors and Ergonomics Society 49th Annual Meeting* (pp. 1200–1204). Santa Monica, CA: Human Factors and Ergonomics Society.

Rantanen, E., & Nunes, A. (2005). Hierarchical conflict detection in air traffic control. *International Journal of Aviation Psychology, 15,* 339–362.

Recarte, M. A., & Nunes, L. M. (2003). Mental workload while driving: Effects on visual search, discrimination and decision-making. *Journal of Experimental Psychology: Applied, 9,* 119–137.

Redding, R. E., Ryder, J. M., Seamster, T. L., Purcell, J. A., & Cannon, J. R. (1991). *Cognitive task analysis of en route air traffic control: Model extension and validation* (Report to the Federal Aviation Administration). McLean, VA: Human Technology. (ERIC Document Reproduction Service No. ED 340 848)

Remington, R. W., Johnston, J. C., Ruthruff, E., Gold, M., & Romera, M. (2000). Visual search in complex displays: Factors affecting conflict detection by air traffic controllers. *Human Factors, 42,* 349–366.

Rodgers, M. D., & Drechsler, G. K. (1993). *Conversion of the CTA, Inc., en route operations concept database into a formal sentence outline job task taxonomy* (Rep. No. DOT/FAA/AM-93/1). Washington, DC: Federal Aviation Administration Office of Aviation Medicine.

Roske-Hofstrand, R., & Murphy, E. D. (1998). Human information processing in air traffic control. In M. W. Smolensky & E. S. Stein (Eds.), *Human factors in air traffic control* (pp. 65–114). San Diego, CA: Academic Press.

Rouse, W. B., Edwards, S. L., & Hammer, J. M. (1993). Modeling the dynamics of mental workload and human performance in complex systems. *IEEE Transactions on Systems, Man, and Cybernetics, 23,* 1662–1670.

Schaefer, D., Meckiff, C., Magill, A., Pirard, B., & Aligne, F. (2001, October). *Air traffic complexity as a key concept for multi-sector planning.* Presented at the Digital Avionics Systems Conference, Daytona Beach, FL.

Schmidt, D. K. (1976). On modeling ATC workload and sector capacity. *Journal of Aircraft, 13,* 531–537.

Schmidt, D. K. (1978). A queuing analysis of the air traffic controller's work load. *IEEE Transactions on Systems, Man, and Cybernetics, SMC-8,* 492–498.

Seamster, T. L., Redding, R. E., Cannon, J. R., Ryder, J. M., & Purcell, J. A. (1993). Cognitive task analysis of expertise in air traffic control. *International Journal of Aviation Psychology, 3,* 257–283.

Sheridan, T. B. (2002). *Humans and automation: System design and research issues.* Santa Monica, CA: Wiley/Human Factors and Ergonomics Society.

Sperandio, J. C. (1971). Variation of operator's strategies and regulating effects on workload. *Ergonomics, 14,* 571–577.
Sperandio, J. C. (1978). The regulation of working methods as a function of workload among air traffic controllers. *Ergonomics, 21,* 195–202.
Stamp, R. G. (1992). *The DORATASK method of assessing ATC sector complexity — An overview* (DORA Communication 8934, Issue 2). London: Civil Aviation Authority.
Stein, E. S. (1985). *Air traffic controller workload: An examination of workload probe* (No. DOT/FAA/CT-TN82/24). Atlantic City International Airport, NJ: Federal Aviation Administration Technical Center.
Weitzman, D. O. (1993). Identifying information processing requirements for air traffic control problem solving: Designing for diversity. In *Proceedings of the Human Factors and Ergonomics Society 37th Annual Meeting* (pp. 103–107). Santa Monica, CA: Human Factors and Ergonomics Society.
Wickens, C. D. (1984). Processing resources in attention. In R. Parasuraman & D. R. Davies (Eds.), *Varieties of attention* (pp. 63–102). New York: Academic Press.
Wickens, C. D. (1992). *Engineering psychology and human performance.* New York: Harper Collins.
Wickens, C. D. (2002). Situation awareness and workload in aviation. *Current Directions in Psychological Science 11,* 128–133.
Wickens, C. D., Mavor, A. S., & McGee, J. P. (1997). *Flight to the future: Human factors in air traffic control.* Washington, DC: National Academy Press.
Willems, B., Allen, R. C., & Stein, E. S. (1999). *Air traffic control specialist visual scanning: 2. Task load, visual noise, and intrusions into controller airspace* (DOT/FAA/CT-TN99/23). Atlantic City, NJ: Federal Aviation Administration.
Wilson, G. F. (2002). An analysis of mental workload in pilots during flight using multiple physiological measures. *International Journal of Aviation Psychology, 12,* 3–18.
Wyndemere, Inc. (1996, October). *An evaluation of air traffic control complexity* (Final Rep.; Contract No. NAS2-14284). Moffett Field, CA: NASA Ames Research Center.

Shayne Loft is a postdoctoral research fellow in the Key Centre for Human Factors and the School of Psychology at The University of Queensland. He received his Ph.D. in psychology in 2004 from the University of Queensland.

Penelope Sanderson is a professor of cognitive engineering and human factors at The University of Queensland, where she directs the Australian Research Council Key Centre for Human Factors. She received her Ph.D. in psychology in 1985 from the University of Toronto.

Andrew Neal is a senior lecturer in the Key Centre for Human Factors and the School of Psychology at The University of Queensland. He received his Ph.D. in cognitive and organizational psychology in 1996 from the University of New South Wales.

Martijn Mooij is a research assistant at the School of Psychology, Key Centre for Human Factors, University of Queensland. He received an M.Sc. in human-machine interaction in 2001 from the Technical University of Eindhoven, Netherlands.

Date received: November 2, 2005
Date accepted: April 5, 2006