Shiftwork, sleep, fatigue and time of day: studies of a change from 8-h to 12-h shifts and single vehicle accidents

Vitale Di Di Milia
University of Wollongong
NOTE

This online version of the thesis may have different page formatting and pagination from the paper copy held in the University of Wollongong Library.

UNIVERSITY OF WOLLONGONG

COPYRIGHT WARNING

You may print or download ONE copy of this document for the purpose of your own research or study. The University does not authorise you to copy, communicate or otherwise make available electronically to any other person any copyright material contained on this site. You are reminded of the following:

Copyright owners are entitled to take legal action against persons who infringe their copyright. A reproduction of material that is protected by copyright may be a copyright infringement. A court may impose penalties and award damages in relation to offences and infringements relating to copyright material. Higher penalties may apply, and higher damages may be awarded, for offences and infringements involving the conversion of material into digital or electronic form.
Chapter Six

Sleepiness and single vehicle accidents
6.1 Introduction

The difficulties in establishing a definitive relationship between sleepiness and industrial accidents were discussed in chapter five. As a result, researchers have turned to the use of alternative data sources. Two areas that have attracted particular interest include, the study of single vehicle road accidents (SVA) and performance errors that are unlikely to lead to accidents (see chapter seven).

Extensive experimental research with humans and animals supports the hypothesis that sleep is driven by a neuro-biological circadian oscillator (Dinges, 1995; Horne, 1988). The human brain is programmed to sleep during the early morning hours, with a secondary less obvious impact during the post lunch period. Sleepiness at night is particularly problematic and most pronounced during the early morning hours (Akerstedt, 1995a).

A number of transport studies have identified the 'parallel' between the sleepiness cycle and accident distribution by time of day (Akerstedt, 1995a; Folkard, 1997; Lauber & Kayten, 1988; Mitler et al. 1988). However, this link has been problematic to demonstrate in industrial studies and this may be explained by the nature of the work. The effect of sleepiness on machine paced or monitoring/vigilance tasks is masked when the technology is reliable and does not require operator input (Mitler et al. 1988). However, industrial studies in which work is more self paced, have shown a link between night performance and accidents (L. Smith et al. 1994).

At least two conditions are necessary to highlight the relationship between sleepiness and accident distribution. The first is identifying a self paced task that is performed across the 24-h period. The second is access to a database that contains a large number of accidents, that are recorded by time of day. Both conditions are met by studying SVA.
Driving is essentially a self-paced tracking task (Maycock, 1997; Summala & Mikkola, 1994). While its behaviour is influenced by a number of psychological and environmental factors, the driver is able to adjust his/her performance. In turn, the consequences of impaired driving, are systematically recorded by police officers in accident reports and stored by statutory bodies. Thus, road accident archives offer a number of strengths:

- error is recorded as a meaningful accident.
- accidents occur in sufficient numbers to enable time of day analysis.
- the archive typically contains a number of other variables that may be used to exclude known factors in accident causation (eg. alcohol, speeding).
- these other variables can be used to provide alternative explanations for performance variability (eg. road type).

Archives however, are not free of methodological problems and require caution, and judicious use. Fundamentally, they generate correlational findings that do not allow causality to be inferred (Cook & Campbell, 1979). There is a strong argument for the use of an experimental approach but in controlling for a range of extraneous factors, the relationship between the variables is compromised.

The advantage of the correlational method is that it seeks to understand the nature of the relationships among the variables in a real-life setting. Hence, it may be regarded to have ecological validity. Well-conducted correlational studies have a place in research, provided they seek to exclude the possibility of counter arguments and limit the tendency to make causal statements. Nonetheless, correlational studies that consistently replicate findings across different contexts, provide a line of evidence to support the presence of a common underlying process.
The present study has two objectives. First, it seeks to replicate earlier findings linking sleepiness as the primary causal factor in SVA by using Australian road accident vehicle data.

The second objective is to examine two potentially alternative explanations for the time of day variability in accident frequency. The first brings together research that demonstrates younger drivers have higher accident rates than older drivers (Pack, Cucchiara, Schwab, Rodgman & Pack 1995; Summala & Mikkola, 1994). This leaves open the possibility that the early morning accident peaks may be due to the greater proportion of younger drivers on the road at these times. The standard correction of accident rates by traffic density does not take into account differences in driver population by time of day. The second alternative explanation for time of day variability in accident frequency is road type. The contribution of road type to accidents has not been extensively explored (Horne & Reyner, 1995a).

This chapter begins with an overview of the main issues in using archival databases, followed by the methodologies used to identify sleepiness in SVA. Estimates and timing of SVA are then presented and followed by a discussion of the methodology used in conducting this study.

6.2 The use of archival data

The use of archival data refers to the use of pre-existing databases (Drury, 1995) for the purpose of third party research. Archival data are typically a rich source of data (Cohen & Manion, 1994), stretching back decades in some cases. As such they allow a truly longitudinal analysis of human behaviour in context (Drury, 1995).

From a methodological perspective archival data can be used in at least three ways:
• to generate hypotheses for subsequent experimental study
• to provide external validity for the conclusions drawn from experimental studies
• to explore phenomena in the field that cannot be subjected to experimental study due to practical and/or ethical reasons (Cohen & Manion, 1994).

The use of archival data is not necessarily straightforward and requires a thorough understanding of its make-up. There are at least two main particular sources of bias (Shaughnessy & Zechmeister, 1985). Since the archive reflects the needs of a particular organization, it only contains 'selective deposits' of information and therefore, seldom directly addresses the research objectives of a third party. For example, sleepiness is not a variable contained in accident databases. Its influence is gauged by the use of proxy variables already in the database. Therefore, it is important that the definition of each variable in the database is clearly understood.

The 'selective survival' of records refers to the possibility that these data are in some way biased. For example, this bias may have occurred during initial recording, during transfer into the archive or during retrieval from the archive.

Of special concern is the possibility of changes in the definition and measurement of the variables over the span of the archive. Changes in the social context surrounding the archive may lead to spurious conclusions. For example, researchers interested in road fatalities would need to note events such as the introduction of random breath testing.

The use of archival data is not without difficulty. However, a thorough understanding of the archives' contents and their rigorous analysis, may result in valuable findings (Bjerner et al. 1955; Horne & Reyner, 1995a).
6.3 Identifying sleepiness in single vehicle accidents

Sleepiness has been investigated using both prospective and retrospective research designs. Both designs have advantages and disadvantages and therefore, have implications for the validity of the results. The choice of design is dependent upon the purpose of the study and practical resource considerations.

6.3.1 Prospective designs

Prospective designs have used three main methodologies; physiological monitoring (Kecklund & Akerstedt, 1993); driving simulators (Lenne, Triggs & Redman, 1997) and check lists to assist in the identification of driver sleepiness (Horne & Reyner, 1995a).

Physiological monitoring provides objective evidence of sleepiness via increases in alpha and theta activity (Akerstedt, 1996). This procedure is well accepted and provides little doubt over the driver's physiological state. Kecklund and Akerstedt (1993) reported an increase in sleepiness as commercial truck drivers drove across the night. Physiological monitoring however, does have some limitations which need to be considered.

Advances in physiological recording have produced miniature devices but these may nonetheless still be obtrusive. Recording electrodes are a constant reminder of being monitored and this may impact on driver behaviour.

Secondly, the reliability of this technology in the field is far from perfect. Kecklund and Akerstedt (1993) excluded four drivers from a sample of 28, due to technical difficulties. It is also possible that subjects may tamper with the equipment so as to avoid being recorded (R. Rosa, personal communication, February 18, 1998).

Perhaps the major limitation is that physiological monitoring does not cater for a large number of subjects over a number of consecutive nights. Studies with small
sample sizes conducted over a single night, have illustrated the presence of sleepiness but they do not allow the findings to be readily generalised.

Driving simulators are particularly useful in that they allow a high degree of experimental control and may provide valuable insights into driver cognition's (Triggs, Drummond & Stanway, 1995). Simulator studies have shown impaired performance at 02.00, 06.00 and at 14.00 (Lenne et al. 1997). These findings are consistent with those from archival studies (Horne & Reyner, 1995a).

Despite the realism and face validity of simulators, their major limitation is that they lack the real life consequences of driving on the road. For example, when subjects in a simulator were asked to stop driving when they felt tired, drivers stopped after 90-240 minutes (Nilsson, Nelson & Carlson. 1997). Outside the laboratory, fatigued drivers are less likely to stop driving, preferring to rest on reaching their destination (Summala & Mikkola, 1994). A police officer (S. Jones, personal communication, December 1, 1997) provided an anecdote of a driver who when stopped for speeding on a long distance journey, responded as being 'too tired to slow down.'

In a prospective study, Horne and Reyner (1995a) provided police officers with a check list as a tool for increasing the reliability of identifying sleepiness in accidents. This aid should assist in more accurately identifying sleepiness. However, the augmented reporting protocol needs to be considered in the light of poor compliance rates (Brown & Di Milia, 1995). In fact, the authors were only able to collect a relatively small number of accidents (n=73), over three months between 1991 and 1994.

6.3.2 Retrospective designs

Retrospective designs rely primarily on two data sources: accident reports completed by police officers and questionnaire surveys of drivers.
The use of archival records is the most common data source for investigating SVA (Horne & Reyner, 1995a; Langlois et al. 1985; Lavie, 1991; Pack et al. 1995; Summala & Mikkola, 1994). These records best provide a sufficiently large database to encompass differences in accident frequency by gender, age, time of day, time of week, environmental factors (eg. weather conditions) and other factors (eg. alcohol) that are associated with road accidents.

The use of archival data needs to be carefully examined. Some of these difficulties were discussed in see section 6.2. Furthermore, archival records do not include information concerning the cognitive, motivational and emotional state of the driver (Triggs et al. 1995).

The major difficulty however, is that accident archives do not directly record sleepiness but are inferred from driver and/or police reports taken at the accident scene. Sleepiness is inferred as the main causal factor by excluding all known possible accident causation variables. This typically results in conservative sleepiness estimates.

Questionnaire survey of drivers may also generate large samples and allows the researcher to ask questions of particular relevance to the hypothesis. However, in common with all surveys, response rates are a source of bias. Moser and Kalton (1971) have argued that the likelihood of biased response rates will increase as the response rate decreases. Maycock (1996) obtained a response rate of 51.3% from a survey of 9,000 drivers and this suggested half the sample may have provided a very different response.

A second difficulty is that questionnaire surveys rely on the accuracy of driver memory and their attributional processes (DeJoy, 1994). Maycock (1996) asked drivers to record their accident involvement over a three year period. A response to this
question depends on the drivers’ interpretation of an accident and their ability to recall the relevant events. Horne and Reyner (1995b) have suggested that accident attribution may be biased, for fear of prosecution or loss of insurance cover.

Prospective (Horne & Reyner, 1995a; Kecklund & Akerstedt, 1993, Lenne et al. 1997) and retrospective (Horne & Reyner, 1995a; Langlois et al. 1985; Lavie, 1991; Pack et al. 1995) studies have both concluded driver sleepiness is an important factor in SVA. The use of either method should depend on the aims of the study. A retrospective design using archival data can be particularly useful when a large data set is needed to demonstrate time of day variation in SVA.

6.3.3 The exclusion method

Sleepiness in SVA is typically identified by excluding other known factors in accident causation from the database. Horne and Reyner (1995a) have provided a good example in applying the exclusion method. The accidents in their analysis met the following criteria:

- blood alcohol levels below the legal limit.
- the vehicle ran off the road for no apparent reason or ran into the back of another vehicle.
- no sign of braking prior to the accident.
- no mechanical defects or burst tyre.
- good weather conditions and clear visibility.
- elimination of speeding and driving too close to the vehicle in front as causes.
- the police officer suspected sleepiness as the prime cause.
- for several seconds before the accident the driver could have seen clearly the point of run off or the vehicle hit.
The exclusion method is not without criticism. It makes the assumption that the database contained all known variables in accident causation. There are at least two factors that may be associated with accidents that are not collected by the New South Wales (NSW, Australia) Road and Traffic Authority (RTA). These are: the effect of other passengers in the vehicle and journey start time and duration.

A SVA need not be necessarily attributed to the driver. Data from the RTA Road Safety Bureau found the driver was alone in 71% of fatigue related crashes (Fell, 1994). Thus there is some possibility that a passenger may play a role in distracting the driver.

Journey start time is clearly associated with accidents. Horne and Reyner (1995a) reported all sleep related accidents involving truck drivers during the early morning occurred within 2-h of the journeys' start. A telephone survey of driver fatigue in the Sydney metropolitan region also reported most accidents occurred within 2-h of journey start (Fell & Black, 1997). Hamelin's (1987) study of truck drivers found accident risk in the first four hours was higher than the subsequent hours, unless drivers had worked for more than 12-hours.

The starting time of a journey has also been implicated in accident risk. Pokorny, Blom and van Leeuwen (1987) reported bus drivers on the morning shift appeared to have a higher accident risk than shifts starting in the afternoon. Despite the actual shift start times, accident risk peaked between the third and fourth hour of both morning and afternoon shift. Feyer and Williamson (1995) reported that short distance drivers reported the earliest fatigue onset.

These studies illustrate the importance of time of day in accident causation. Of course, time of day and time on task interact. The key point is that setting maximum working hours in the transport industries has not proved effective (Tepas, 1994).
The exclusion method is not unproblematic. However, the removal of as many accident causation factors as possible, does increase the likelihood that sleepiness may be the main explanatory variable. The exclusion method results in conservative estimates of sleepiness, since it is reasonable to suggest that some proportion of accidents involving other factors may nonetheless have been primarily caused by sleepiness.

6.4 Sleepiness in single vehicle accidents

6.4.1 Estimates of sleepiness in single vehicle accidents

Sleepiness estimates show considerable variation. These differences appear to be related to the data source, research design, the method used to identify sleepiness, and with the type of accidents being examined.

Sleepiness estimates have shown much variability within retrospective studies. Accidents due to falling asleep (excluding intoxication) accounted for 0.46% of SVA in North Carolina (Pack et al. 1995). Maycock (1995, cited in Maycock, 1996) used police reports from several English counties, to calculate that between 0.5% and 3.7% of accidents were attributable to falling asleep at the wheel. Horne and Reyner (1995a) estimated 16% of accidents from all roads in south-west England were sleepiness related.

These variances may reflect: (a) differences in the make-up/use of archival data and accident reporting between countries; (b) the difficulty (Maycock, 1996) and/or reluctance (J. Horne, personal communication, November 21, 1997) of police officers to identify sleep or fatigue as the cause of the accident; and (c) the use of different criteria to infer sleepiness.

Horne and Reyner's (1995a) prospective study based solely on motor-ways, estimated sleepiness at 23%. In this study, police were provided with a check list to
assist in the identification of sleepiness and this design, would suggest a better measure of sleepiness.

Studies using sleepiness related concepts have also produced varying estimates. Maycock’s (1996) self report survey, found ‘tiredness’ was implicated in 9-10% of all accidents. Tiredness was also the fifth highest factor in accident causation. The RTA reported ‘fatigue’ (see section 6.7.1) accounted for 6% of all accidents and for 15% of all fatal accidents in 1992. Zulley et al. (1994) concluded that 24% of 204 fatal accidents on German highways were due to falling asleep.

Sleepiness is estimated as a causal factor in 0.46% to 24% of SVA. These higher estimates are in line with prospective EEG studies. Torsvall and Akerstedt (1987) reported 25% of train drivers on the night shift showed EEG patterns consistent with sleepiness.

6.4.2 Timing of sleepiness related single vehicle accidents

The timing of SVA has shown consistent findings across a number of countries. Horne and Reyner (1995a) reported three accident peaks for all roads in south-west England over a six year period; 02.00, 06.00 and 16.00. Their prospective study, found the highest accident frequency between 00.00-02.59, with daytime accidents peaking between 15.00-17.59. In Texas, accidents over a four year period showed peaks in rural areas between 02.00-03.00 and for urban areas between 03.00-04.00 (Langlois et al. 1985). Sleepiness related accidents in Israel over a six year period also showed peaks at 03.00 and 15.00 (Lavie, 1991).

The timing of sleepiness road accidents is maintained when adjustments are made for distance travelled (Hamelin, 1987) and differences in traffic density (Horne & Reyner, 1995b). Of note, is that SVA are highest in the early morning hours when traffic density is lowest (Horne & Reyner, 1995a). Studies that have adjusted accident
distribution for traffic density report a main accident peak between 02.00 to 04.00 and a smaller accident peak between 16.00 and 17.59 (Horne & Reyner, 1995b; Langlois et al. 1985).

The timing of accidents has also been shown to be age related. Summala and Mikkola (1994) reported accidents involving 18-20 year olds peaked between 00.00 and 06.00, whereas drivers 56 years old and over showed a peak for accidents in the late afternoon. Pack et al. (1995) have reported a similar age difference for time of day accident peaks.

6.4.3 Correcting accident frequency for variation in traffic density

Accident distribution for SVA is typically adjusted for the variation in traffic density across the 24-h (Langlois et al. 1985). While this adjustment is necessary, it has some conceptual and methodological limitations.

At a conceptual level, the underlying argument is that the accident rate is exposure related. Thus as traffic volume increases, so does the accident rate. While this argument has some support, it is an incomplete explanation. Horne and Reyner (1995a) found a positive relationship between afternoon accidents and high traffic density but not for early morning accidents. Furthermore, increases in afternoon traffic density can mask the true effect of sleepiness. Other drivers may serve to increase the level of sensory stimulation, so that alertness is maintained (Akerstedt & Landstrom, 1998).

SVA are also subject to variations in traffic density. However, in their case, the 'exposure' argument must also consider the logic that night time accidents are more likely to be single vehicles, since there are fewer vehicles on the road. Furthermore, decreased traffic density may be associated with decreased stimulation.
Traffic density is also problematic because it does not consider differences in the driver population by time of day. There is considerable evidence supporting an argument for marked differences in accident risk associated with driver age and gender (see section 6.4.4). Furthermore, time of day corrections for traffic density do not consider factors such as journey length. Typically longer journeys include the night hours (Hamelin, 1987; Summala & Mikkola, 1994) where accident risk may be compounded by time on task effects.

Traffic density also has at least two methodological difficulties that limit the accuracy of the estimate; the recording instrument and the location of the recording instrument.

Traffic density is typically recorded by mechanical or electrical (sensor) counters. These devices do not equally discriminate. Mechanical counters register the number of axles and not the number of vehicles. Electronic sensors on the other hand, record the passing of an object. Therefore, they also do not readily identify vehicle types (e.g. cars, trailers, motor-cycles and bicycles).

The location of sensors (or observers) is also critical to the accuracy of traffic density estimates. For example, wide differences are obtained from devices placed on main or secondary roads and whether they record inbound traffic, outbound traffic or both. Traffic density estimates show variation by day of week and holiday periods (Langlois et al. 1985; RTA, 1994). Such details have not been reported in studies.

In an applied situation, it is typically difficult to obtain traffic density data specific to the accident region being examined. For example, Horne and Reyner (1995a) applied national traffic density estimates to accidents that occurred in south-west England. Langlois et al. (1985) has also noted that in some rural areas it may not be possible to obtain accurate estimates of traffic density.
6.4.4 Driver characteristics and accident risk

The role of driver age and gender in accident risk has been documented in a number of studies. Drivers under 25 years of age have the greatest accident risk and males have a greater risk than females in all age groups (Fell, 1994; Horne & Reyner, 1995a; Pack et al. 1995).

The accident risk for Swedish males 18-19 years of age, has been reported to be eight times greater than males 25-54 years of age (Brorsson, Rydgren & Ifver, 1993). Summala and Mikkola (1994) reported Finnish drivers aged between 18-20 are over represented in early morning accidents, while drivers over 56 years of age are over represented in afternoon accidents. They surmised that as driver age increases, the frequency of night time accidents decreases, while day time accidents increase.

In general, male drivers are involved in more accidents than females, but are also over represented in accidents attributed to sleepiness and fatigue; males have accounted for 82%-92% of SVA (Horne & Reyner, 1995a); 74.5% of ‘fall-asleep’ accidents (Pack et al. 1995); and 84% of fatigue related accidents (Fell, 1994).

Accident risk has also been demonstrated to increase at the weekend (Langlois et al. 1985). Brorsson et al. (1993) estimated the risk of a SVA was 40 times greater on Friday and Saturday night compared to the rest of the week. There is good evidence showing younger male drivers are also over represented on the roads at the weekend and at night (Horne & Reyner, 1995b; Pack et al. 1995; Summala & Mikkola, 1994).

A number of explanations have been advanced to explain the increased accident risk in younger drivers at night. Road use appears to reflect age related lifestyle differences (Horne & Reyner, 1995a, 1995b; Pack et al. 1995). Younger drivers are more likely to be out at night and on the weekends (Langlois et al. 1985). Lang,
Waller and Shope (1996) found the higher rate of SVA in males was related to their increased driving frequency and misuse of alcohol and marijuana. It may also be that younger drivers are more impaired by sleepiness in the early morning (Brendel et al. 1990).

Age and driving experience are highly correlated and it has been suggested novice drivers under estimate driving risk, especially at night. Younger male drivers are more likely to continue driving when fatigued (Summala & Mikkola, 1994), engage in unsafe driving, drinking, speeding and breaking the conditions of restricted licences (Harre, Field & Kirkwood, 1996). Wikman, Nieminen and Summala (1998) found novice drivers made inefficient use of peripheral vision and tended to take their eyes off the road for longer periods when attending to tasks such as tuning a radio. These periods were also associated with greater lane drift.

The conclusions that younger drivers make more use of the road at night and on weekends are not necessarily empirically based. They tend to be inferred from their accident rates by time of day. The relationship between driver characteristics and road accidents by time of day is difficult to examine because detailed information on these variables is not available. Brorsson et al. (1993) is a rare study that used census data to examine accident rates.

Nonetheless, the literature suggests there are differences in road use by time of day and day of the week by driver characteristics. This suggests that adjusting accident distribution by driver characteristics (including day of the week) may provide a better measure than traffic density. A proposal for adjusting accident distribution by driver characteristics can be found in section 6.7.4.3.
6.5 Shiftwork and driving risk

Concern for shiftworker well-being is an issue both at work and away from work (Rosa & Bonnet, 1993). The effects of acute or chronic sleep loss are most likely to be seen during and following night shift (Tepas & Mahan, 1989). A number of self report studies have linked sleep loss, night work and long work hours, with vehicle accidents.

Fell and Black (1997) surveyed 178 drivers involved in city driving accidents, with a control group of 101 accident free drivers. They found 57% of the accident drivers did not have a full night sleep prior to the accident. Long working hours (overtime), working night shift, or leaving home early in the morning to go to work were cited by 55% of drivers reporting sleep loss. Furthermore, 28% of accident drivers reported working some form of shiftwork.

Richardson, Miner and Czeisler (1990) found 21.7% of continuous shiftworkers reported at least one vehicle accident or near miss that they attributed to sleepiness in the previous 12 months. In contrast only 7.2% of dayworkers reported such an incident. A random survey of 1000 New York drivers (McCartt, Pack & Ribner, 1995), found 43% reported drowsiness when driving and attributed their drowsiness to night/evening work, working overtime, working more than one job, and working rotating shiftwork in the previous seven day period.

6.6 Objectives for this study

This study has two main objectives. The first objective is to conduct a time of day analysis of sleepiness related SVA in NSW and to compare these results with those from Horne and Reyner (1995b).

The second objective has two parts. The first is to explore the accident data by driver characteristics (ie. age, gender and day of week) and to develop a new
measure for adjusting accident distribution as an alternative to using traffic density. The second objective is to examine the role of road type on single vehicle accident frequency.

6.7 Method

6.7.1 A description of the RTA archive

The aims of this study were discussed with the RTA. This discussion identified 'fatigue' from their archive, as the best starting point in collecting a data set suited to investigate sleepiness in SVA. According to the RTA:

*For fatigue to be identified as the causal factor, one or both of the following criteria must be satisfied;*

(a) *The vehicle's controller was described by police as being asleep, drowsy or fatigued.*

(b) *The vehicle performed a manoeuvre which suggested loss of concentration of the controller due to fatigue, that is*

(i) *the vehicle travelled onto the incorrect side of a straight road and was involved in a head-on collision (and was not overtaking another vehicle and no other relevant factor was identified);* or

(ii) *the vehicle ran off a straight road or off the road to the outside of a curve and the vehicle was not directly identified as travelling at excessive speed and there was no other relevant factor identified in the manoeuvre (1995, p. xiv).*

The RTA supplied a data set for the period 1992-1996 inclusive. The database contained all fatigue related accidents, excluded those due to speeding and blood alcohol concentration (BAC) above 0.05 (n=13,682).
Additional variables from the archive were also obtained in order to further exclude the possibility of their involvement in the accident. These variables included:

- number of vehicles involved.
- weather conditions; eg. rain, fog/mist.
- road surface conditions; eg. wet, snow/ice.
- urbanisation; metropolitan, country urban and country non-urban.

The following variables were also collected and used to investigate their relationship with sleepiness:

- age.
- gender.
- time of day.
- day of accident.
- accident severity (tow-away, minor (non-admission to hospital), major (hospital admission), fatality).
- road classification (unclassified, other classified, state highway, freeway/motorway).
- type of vehicle involved (eg. car, light truck).

6.7.2 Design of study

The database from the RTA contained all fatigue related accidents that already excluded speeding and BAC above 0.05. The method of exclusion was subsequently applied to the database. The final data set contained accidents that met these and the following criteria:

- only single vehicles were involved.
- the weather was recorded as fine or overcast only.
the road surface was dry.

drivers were at and above the legal driving age (≥ 17).

contained only accidents in urban areas (Sydney, Newcastle and Wollongong - population approximately 4.5 million). This served to mitigate the difference between urban and rural driving (Langlois et al. 1985) and to increase the applicability of the traffic density estimates.

6.7.3 Traffic density

Traffic density data was based on hourly traffic movements in two main Sydney traffic zones. The mean of the inbound and outbound traffic movements at both sites, provided a general estimate for traffic density based on 1991 traffic flow. These estimates were described as 'the only comprehensive data available' (RTA, 1994, p. 32).

6.7.4 Data treatment

i. Variable manipulation

In order to examine the role of driver characteristics, a number of variables were grouped. Driver age and day of accidents were reclassified as:

- <30yo - drivers under 30 years of age.
- 30+yo - drivers 30 years of age and over.
- W-END - these were all accidents from 19.00 on Friday to 05.99 on Monday.
- W-DAY - these were accidents form 06.00 on Monday to 18.99 on Friday.

These classifications together with gender, provided eight separate driver characteristic groups through which accident frequency could be examined:

- <30yo Male W-END.
The road classification variables were also reclassified to allow for analysis of road type and SVA. The groupings were:

- Unclassified - these roads carried local suburban traffic.
- Main - all other classified roads, state highway and freeway/motorway.

**ii. Traffic density**

The single vehicle accident distribution was adjusted for traffic density, using the following steps (see also Horne & Reyner, 1995b).

1. The accident frequency at each hour was divided by the traffic density estimate for the same hour.

2. These values were subsequently expressed as probabilities. This was achieved by summing the adjusted values and dividing each hourly estimate by the sum.

3. The sum of these probabilities (step 2) equals one.

**iii. Driver characteristics**

The limitations of traffic density were discussed earlier. However, there are no available national, state or regional data on road use by age, gender and day of week that could be used as an alternative to traffic density. Brorsson et al. (1993) reported a rare study using a 1984 Swedish national survey to investigate driver behaviour.
In the absence of road usage norms, it was decided to use the accident distribution data itself, to adjust the accident frequency for the eight driver characteristic groups. The solution involves weighting the total accident frequency for each hour, for the contribution of each driver characteristic group.

The weighting procedure assumes that at each time of day, the accident frequencies reflect in large part, road use by each driver characteristic group. From this premise, the raw single vehicle accident frequency was adjusted using the following steps:

1. For each hour of the day, the contribution of each driver characteristic group to the total accident frequency was calculated in percentage terms.

2. The accident frequency for each driver characteristic group was weighted by its contribution to the total. The sum of these weighted frequencies represents an estimate in which each driver characteristic group is equally represented. An example of this procedure is illustrated in table 6.1.

The data produced by these calculations serve as heuristic values.

Table 6.1

<table>
<thead>
<tr>
<th>Time - 12.00</th>
<th>Accident frequency</th>
<th>Percentage</th>
<th>Frequency X percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Driver Characteristic A</td>
<td>150</td>
<td>63</td>
<td>9450</td>
</tr>
<tr>
<td>Driver Characteristic B</td>
<td>60</td>
<td>25</td>
<td>1500</td>
</tr>
<tr>
<td>Driver Characteristic C</td>
<td>30</td>
<td>12</td>
<td>360</td>
</tr>
<tr>
<td>Total</td>
<td>240</td>
<td>100</td>
<td>11310</td>
</tr>
</tbody>
</table>
iv. Road type

In the absence of specific traffic density data for each road type, the impact of differences in road type can only be examined by plotting uncorrected accident frequencies.

6.8 Results

6.8.1 Descriptive statistics for single vehicle accidents

The mean driver age for SVA was 31.1 years (SD = 15.0) and the mode was 18 years (n=203). Males were involved in three-quarters of the accidents (76.5%). A fuller description of the SVA attributable to sleepiness is shown in table 6.2.

Insert table 6.2

These accidents resulted in; 36 deaths, 402 hospital admissions, 783 non-admissions to hospital and 1,653 vehicle tow-aways. Males accounted for 30 deaths. Nine of these deaths resulted from accidents between 03.00-06.59.

6.8.2 Accident distribution and traffic density

Figure 6.1 shows traffic density and the number of sleepiness accidents by time of day. The figure shows a bi-modal pattern with accident frequency highest at 04.00 and a smaller peak at 15.00. The early morning accident peak coincided with the lowest traffic density, although the afternoon accident peak was associated with high traffic density.

Insert figure 6.1

Figure 6.2 shows the probability of a sleepiness accident, adjusted for traffic density from the present study and those obtained by Horne and Reyner (1995b). These probabilities sum to one, allowing comparisons to be made. The two curves show a very similar time of day distribution, with the present study showing an accident peak 1-h later at 03.00. The inset in figure 6.2 also shows elevated probabilities during
Table 6.2
Descriptive Statistics for Single Vehicle Accidents

1. Estimate of single vehicle accidents attributable to sleepiness

<table>
<thead>
<tr>
<th></th>
<th>Number</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single vehicle accidents (n = 256,572)</td>
<td>2874</td>
<td>1.12</td>
</tr>
</tbody>
</table>

2. Driver characteristics for single vehicle accidents (n = 2650)

<table>
<thead>
<tr>
<th></th>
<th>Number</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weekend accidents</td>
<td>1187</td>
<td>44.80</td>
</tr>
<tr>
<td>Weekday accidents</td>
<td>1463</td>
<td>55.20</td>
</tr>
<tr>
<td>Male drivers</td>
<td>2026</td>
<td>76.50</td>
</tr>
<tr>
<td>Female drivers</td>
<td>624</td>
<td>23.50</td>
</tr>
<tr>
<td>Drivers aged &lt;30yo</td>
<td>1609</td>
<td>60.70</td>
</tr>
<tr>
<td>Drivers aged 30+yo</td>
<td>1041</td>
<td>39.30</td>
</tr>
</tbody>
</table>

3. Vehicle types involved in single vehicle accidents (n=2874).

<table>
<thead>
<tr>
<th></th>
<th>Number</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cars</td>
<td>2535</td>
<td>88.20</td>
</tr>
<tr>
<td>Light trucks</td>
<td>133</td>
<td>4.63</td>
</tr>
<tr>
<td>Motorcycles</td>
<td>110</td>
<td>3.83</td>
</tr>
<tr>
<td>Other motor vehicles</td>
<td>38</td>
<td>1.32</td>
</tr>
<tr>
<td>Heavy rigid trucks</td>
<td>23</td>
<td>0.80</td>
</tr>
<tr>
<td>Articulated trucks</td>
<td>21</td>
<td>0.73</td>
</tr>
<tr>
<td>Buses</td>
<td>7</td>
<td>0.24</td>
</tr>
<tr>
<td>Emergency vehicles</td>
<td>7</td>
<td>0.24</td>
</tr>
</tbody>
</table>

(Cont.)
Descriptive Statistics for Single Vehicle Accidents (cont.)

4. Single vehicle accidents by days of the week (n=2874).

<table>
<thead>
<tr>
<th>Day</th>
<th>Number</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Monday</td>
<td>362</td>
<td>12.60</td>
</tr>
<tr>
<td>Tuesday</td>
<td>303</td>
<td>10.54</td>
</tr>
<tr>
<td>Wednesday</td>
<td>353</td>
<td>12.28</td>
</tr>
<tr>
<td>Thursday</td>
<td>373</td>
<td>12.98</td>
</tr>
<tr>
<td>Friday</td>
<td>375</td>
<td>13.05</td>
</tr>
<tr>
<td>Saturday</td>
<td>551</td>
<td>19.17</td>
</tr>
<tr>
<td>Sunday</td>
<td>557</td>
<td>19.38</td>
</tr>
</tbody>
</table>

5. Single vehicle accidents by road type (n=2874).

<table>
<thead>
<tr>
<th>Category</th>
<th>Number</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unclassified</td>
<td>1491</td>
<td>51.88</td>
</tr>
<tr>
<td>Other classified</td>
<td>885</td>
<td>30.80</td>
</tr>
<tr>
<td>State highway</td>
<td>347</td>
<td>12.07</td>
</tr>
<tr>
<td>Freeway/motorway</td>
<td>151</td>
<td>5.25</td>
</tr>
</tbody>
</table>

the day hours for the Australian data and both plots showed post-lunch increases in accident probability. A comparison of maximum and minimum accident probability suggests that risk was 22.8 times higher at 03.00 (\(P = 0.205\)) compared to 10.00 (\(P = 0.009\)). Accident risk between the afternoon accident peak at 14.00 (\(P = 0.014\)) and 10.00 suggests the afternoon period was 1.6 times more likely to result in an accident.

Insert figure 6.2
Figure 6.1. The relationship between sleepiness accidents and traffic density by time of day.
Figure 6.2. Comparative probabilities for sleepiness accidents between the present study and those from Horne & Reyner (1995b). Inset: Enlargement of the 06.00-20.00 section.
6.8.3 An examination of driver characteristics by time of day

The accident frequency distributions by time of day for age, gender and day of
week categories are shown in Figures 6.3, 6.4 and 6.5.

Insert figures 6.3, 6.4, 6.5

Figure 6.3 shows that for drivers <30yo, accident frequency peaked at 03.00.

For drivers' 30+yo, accident frequency peaked 12-h later at 15.00.

Accident frequency by gender is shown in figure 6.4. Males showed a
pronounced peak at 04.00 and a smaller peak at 15.00. In contrast, females showed a
single but much higher peak at 15.00, followed by a sharp decline.

Figure 6.5 shows accident frequency for W-END and W-DAY. A marked peak
at 03.00 and a smaller peak at 17.00 was found for W-END. In sharp contrast, W-DAY
accidents showed a large afternoon peak at 15.00 but not an early morning peak.

A detailed breakdown of accident frequency by the driver characteristic
groups can be found in appendix four.

6.8.4 Statistical analyses of driver characteristics

The descriptive statistics for the driver characteristic groups are shown in
table 6.3. The data shown in table 6.3 were adjusted for the difference in the number of
days between W-END and W-DAY. The eight driver characteristics means showed
some large variances between the groups and may reflect differences in sample sizes.
Such variances suggested the use of non-parametric statistics.

Insert table 6.3

Differences within the driver characteristic groups were examined using the
Wilcoxon signed rank test (Siegel & Castellan, 1988). Due to many comparisons
Figure 6.3. Accident frequency distribution by driver age categories.
Figure 6.4. Accident frequency distribution by gender categories.
**Figure 6.5**. Accident frequency distribution by day of week categories.
Table 6.3

Descriptive Statistics for Driver Characteristics

<table>
<thead>
<tr>
<th>Driver Characteristics</th>
<th>N*</th>
<th>Mean**</th>
<th>SD**</th>
<th>SE**</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;30yo, Male, W-END</td>
<td>663</td>
<td>9.21</td>
<td>5.86</td>
<td>1.20</td>
</tr>
<tr>
<td>&lt;30yo, Male, W-DAY</td>
<td>630</td>
<td>6.56</td>
<td>1.40</td>
<td>0.29</td>
</tr>
<tr>
<td>&lt;30yo, Female, W-END</td>
<td>157</td>
<td>2.18</td>
<td>1.16</td>
<td>0.24</td>
</tr>
<tr>
<td>&lt;30yo, Female, W-DAY</td>
<td>159</td>
<td>1.66</td>
<td>0.72</td>
<td>0.15</td>
</tr>
<tr>
<td>30+yo, Male, W-END</td>
<td>274</td>
<td>3.81</td>
<td>1.63</td>
<td>0.33</td>
</tr>
<tr>
<td>30+yo, Male, W-DAY</td>
<td>459</td>
<td>4.78</td>
<td>2.13</td>
<td>0.43</td>
</tr>
<tr>
<td>30+yo, Female, W-END</td>
<td>93</td>
<td>1.29</td>
<td>0.54</td>
<td>0.11</td>
</tr>
<tr>
<td>30+yo, Female, W-DAY</td>
<td>215</td>
<td>2.24</td>
<td>1.54</td>
<td>0.31</td>
</tr>
</tbody>
</table>

* N refers to the adjusted number of accidents due to differences in the number of days between the W-END and W-DAY categories.

** Descriptive statistics describe the mean number of accidents per day.

possible, it was decided to explore the differences by age split (ie. <30yo and 30+yo).

Nonetheless, because twelve between group tests were required, alpha was set at 0.005, even though such adjustment is not necessary with non-parametric tests. These means are shown in table 6.4.

For drivers <30yo there were no significant within gender differences for accident frequencies between W-END and W-DAY at the 0.005 level. However, there were significant between gender differences for W-END and W-DAY, with males showing a significantly higher accident rate.
Table 6.4
Wilcoxon Statistics Split by Driver Age for Mean Accident Rate by Gender and Day of Week Category

<table>
<thead>
<tr>
<th>Comparison</th>
<th>Drivers aged &lt;30 years old</th>
<th>Drivers aged 30+ years old</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Mean</td>
</tr>
<tr>
<td>A</td>
<td>B</td>
<td>$p$</td>
</tr>
<tr>
<td>MW-END</td>
<td>MW-DAY</td>
<td>9.21</td>
</tr>
<tr>
<td>MW-END</td>
<td>FW-END</td>
<td>9.21</td>
</tr>
<tr>
<td>MW-END</td>
<td>FW-DAY</td>
<td>9.21</td>
</tr>
<tr>
<td>MW-DAY</td>
<td>FW-END</td>
<td>6.56</td>
</tr>
<tr>
<td>MW-DAY</td>
<td>FW-DAY</td>
<td>6.56</td>
</tr>
<tr>
<td>FW-END</td>
<td>FW-DAY</td>
<td>2.18</td>
</tr>
</tbody>
</table>

Key: M = males; F = females; W-END = weekend; W-DAY = weekday.
For female drivers aged 30+yo, there were significantly more W-DAY accidents than W-END accidents but for males, these differences were not significant. For both W-DAY and W-END, males had significantly more accidents than females. In the absence of road use norms by gender, it is necessary to make the assumption that gender is equally represented on the road by time of day.

6.8.5 Within age group comparison of driver characteristics

i. Drivers <30yo by gender at W-END.

The time of day accident distribution for drivers <30yo by gender at the W-END is shown in figure 6.6. The two distributions show a similar accident rate increase in the early morning hours with a peak 03.00. From 08.00 to 15.00 females registered more accidents than males, whilst males accounted for more accidents between 17.00 and 23.00.

Insert figure 6.6.

ii. Drivers <30yo by gender at W-DAY.

This comparison suggested neither males or females showed a clear accident peak for the early morning hours (see figure 6.7). However, males did show a bi-modal distribution with an early morning (04.00) and afternoon peak (16.00). Female accident distribution showed two clear day time peaks at 09.00 and 15.00. In general, males recorded more evening and night time accidents with females prominent during the day time accidents.

Insert figure 6.7.

iii. Drivers 30+yo by gender at W-END.

For this group, the time of day variability was far less clear for males and females. Generally, males had more accidents across the night with the accident peak occurring at 04.00. Females again showed more day time accidents with peaks at
Figure 6.6. Accident frequency distribution for drivers aged <30yo during W-END by gender.
Figure 6.7. Accident frequency distribution for drivers aged <30yo during W-DAY by gender.
10.00 and 15.00 (see figure 6.8).

Insert figure 6.8.

**iv. Drivers 30+yo by gender at W-DAY.**

For this comparison, neither gender showed an early morning accident peak but both recorded a clear accident peak between 14.00 and 15.00. In general, males dominated the early morning accidents and females dominated the day time accident rate (see figure 6.9).

Insert figure 6.9.

**6.8.6 Weighting accident frequency for driver characteristics**

The effect of weighting the accident frequency by driver characteristics can be seen in figure 6.10. A clear bi-modal accident peak was found at 03.00 and at 15.00.

Insert figure 6.10.

Figure 6.11 expresses the accident risk probability for each hour of the day when the data were weighted by the driver characteristic groups. Once again, a bi-modal distribution was observed with the highest accident probability being recorded at 03.00 ($P = 0.25$) and at 14.00 ($P = 0.01$).

Insert figure 6.11

**6.8.7 The contribution of weighted driver characteristics to early morning and afternoon accident frequency**

The contribution from each driver characteristic group to figure 6.11 is shown in table 6.5 in percentage terms. It shows a high percentage of male drivers <30yo in early morning accidents. The afternoon accident rate seems to reflect midweek accidents by male drivers in both age groups and female drivers 30+yo.

Insert table 6.5
Figure 6.8. Accident frequency distribution for drivers aged 30+yo during W-END by gender.
Figure 6.9. Accident frequency distribution for drivers aged 30+yo during W-DAY by gender.
Figure 6.10. Accident frequency distribution by time of day when weighted for driver characteristics.
Figure 6.11. Comparative probabilities for sleepiness accidents when adjusted for driver characteristics. Inset: Enlargement of the 06.00-20.00 section.
Table 6.5

The Contribution of Weighted Driver Characteristics to Accidents Between 02.00-05.00 and 14.00-17.00 (% shown)

<table>
<thead>
<tr>
<th></th>
<th>DC</th>
<th>02.00</th>
<th>03.00</th>
<th>04.00</th>
<th>05.00</th>
<th>14.00</th>
<th>15.00</th>
<th>16.00</th>
<th>17.00</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;30yo M-END</td>
<td>39.70</td>
<td>47.10</td>
<td>42.60</td>
<td>42.50</td>
<td>9.30</td>
<td>7.09</td>
<td>8.55</td>
<td>23.70</td>
<td></td>
</tr>
<tr>
<td>&lt;30yo M-DAY</td>
<td>25.00</td>
<td>21.70</td>
<td>21.60</td>
<td>24.40</td>
<td>20.90</td>
<td>24.10</td>
<td>29.10</td>
<td>22.90</td>
<td></td>
</tr>
<tr>
<td>&lt;30yo F-END</td>
<td>10.30</td>
<td>10.10</td>
<td>16.90</td>
<td>7.87</td>
<td>3.10</td>
<td>4.96</td>
<td>1.71</td>
<td>3.39</td>
<td></td>
</tr>
<tr>
<td>&lt;30yo F-DAY</td>
<td>4.30</td>
<td>4.40</td>
<td>8.11</td>
<td>10.20</td>
<td>7.75</td>
<td>8.51</td>
<td>5.13</td>
<td>7.63</td>
<td></td>
</tr>
<tr>
<td>30+yo M-END</td>
<td>7.80</td>
<td>11.60</td>
<td>6.08</td>
<td>7.87</td>
<td>10.90</td>
<td>8.51</td>
<td>9.40</td>
<td>7.63</td>
<td></td>
</tr>
<tr>
<td>30+yo M-DAY</td>
<td>6.00</td>
<td>2.20</td>
<td>1.60</td>
<td>2.70</td>
<td>29.50</td>
<td>26.20</td>
<td>28.20</td>
<td>20.30</td>
<td></td>
</tr>
<tr>
<td>30+yo F-END</td>
<td>4.30</td>
<td>2.90</td>
<td>0.70</td>
<td>2.70</td>
<td>3.88</td>
<td>5.67</td>
<td>4.27</td>
<td>5.93</td>
<td></td>
</tr>
<tr>
<td>30+yo F-DAY</td>
<td>2.60</td>
<td>0.00</td>
<td>2.70</td>
<td>2.70</td>
<td>14.70</td>
<td>14.90</td>
<td>13.70</td>
<td>8.47</td>
<td></td>
</tr>
<tr>
<td>Total*</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td></td>
</tr>
</tbody>
</table>

Key: DC = Driver characteristics; * Due to rounding of numbers, column totals may not equal 100.
6.8.8 The contribution of unweighted driver characteristics to early morning and afternoon accident frequency

Table 6.6a (02.00 to 05.00) and table 6.6b (14.00 to 17.00) show the percentage of accidents for each of the driver characteristics. If the probability for an accident rate were constant across the day, 4.17% of accidents would be expected each hour or 16.68% for the four hour blocks shown in tables 6.6a and 6.6b.

Table 6.6a shows that for each hour in the early morning, drivers aged <30yo with the exception of females on W-DAY registered accidents above chance levels.

Table 6.6b shows that for each hour of the afternoon, females aged 30+yo for both W-END and W-DAY and males in both age groups during the W-DAY registered accidents above chance levels.

6.8.9 Accident frequency by road type

Unclassified roads accounted for 51.9% of SVA and main roads accounted for 48.1% of SVA. The time of day accident distribution for each road type are shown in figure 6.12.

A chi-square test of accident distribution between unclassified and main roads showed a significant difference ($\chi = 53.67, df = 23, p = 0.0003$) but this test does not locate the difference. Visual inspection of the two distributions suggested the difference may be between 02.00 to 06.00. However, a chi-square test for this period showed no significant differences ($\chi = 2.04, df = 4, p = 0.73$).

A breakdown of the accidents between 02.00 and 06.00 by driver characteristics (see table 6.7) showed the majority of accidents, involved male drivers <30yo at the W-END on main roads, followed by the same group during the W-DAY on
Table 6.6a

The Percentage of Accidents by Unweighted Driver Characteristics to Accidents Between 02.00 and 05.00

<table>
<thead>
<tr>
<th>Driver Characteristics</th>
<th>02.00</th>
<th>03.00</th>
<th>04.00</th>
<th>05.00</th>
<th>Total*</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;30 M W-END</td>
<td>6.94</td>
<td>9.80</td>
<td>9.50</td>
<td>8.14</td>
<td>34.38</td>
</tr>
<tr>
<td>&lt;30 M W-DAY</td>
<td>4.60</td>
<td>4.76</td>
<td>5.08</td>
<td>4.92</td>
<td>19.36</td>
</tr>
<tr>
<td>&lt;30 F W-END</td>
<td>5.73</td>
<td>10.19</td>
<td>5.73</td>
<td>6.37</td>
<td>28.02</td>
</tr>
<tr>
<td>&lt;30 F W-DAY</td>
<td>4.40</td>
<td>1.89</td>
<td>1.26</td>
<td>1.89</td>
<td>9.44</td>
</tr>
<tr>
<td>30+ M W-END</td>
<td>4.38</td>
<td>5.11</td>
<td>9.12</td>
<td>3.65</td>
<td>22.26</td>
</tr>
<tr>
<td>30+ M W-DAY</td>
<td>1.09</td>
<td>1.31</td>
<td>2.61</td>
<td>2.83</td>
<td>7.84</td>
</tr>
<tr>
<td>30+ F W-END</td>
<td>5.38</td>
<td>4.30</td>
<td>1.08</td>
<td>3.23</td>
<td>13.99</td>
</tr>
<tr>
<td>30+ F W-DAY</td>
<td>1.40</td>
<td>0.00</td>
<td>1.86</td>
<td>1.40</td>
<td>4.66</td>
</tr>
</tbody>
</table>

* Sum of the four time points. The expected percentage of total accidents for these time points is 16.68%.
Table 6.6b

The Percentage of Accidents by Unweighted Driver Characteristics to Accidents Between 14.00 and 17.00

<table>
<thead>
<tr>
<th>Driver Characteristics</th>
<th>14.00</th>
<th>15.00</th>
<th>16.00</th>
<th>17.00</th>
<th>Total*</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;30 M W-END</td>
<td>1.81</td>
<td>1.51</td>
<td>1.51</td>
<td>4.22</td>
<td>9.05</td>
</tr>
<tr>
<td>&lt;30 M W-DAY</td>
<td>4.29</td>
<td>5.40</td>
<td>5.40</td>
<td>4.29</td>
<td>15.98</td>
</tr>
<tr>
<td>&lt;30 F W-END</td>
<td>2.55</td>
<td>4.46</td>
<td>1.27</td>
<td>2.55</td>
<td>10.83</td>
</tr>
<tr>
<td>&lt;30 F W-DAY</td>
<td>6.29</td>
<td>7.55</td>
<td>3.77</td>
<td>5.66</td>
<td>23.27</td>
</tr>
<tr>
<td>30+ M W-END</td>
<td>5.11</td>
<td>4.38</td>
<td>4.01</td>
<td>3.28</td>
<td>16.78</td>
</tr>
<tr>
<td>30+ M W-DAY</td>
<td>8.28</td>
<td>8.06</td>
<td>7.19</td>
<td>5.23</td>
<td>28.76</td>
</tr>
<tr>
<td>30+ F W-END</td>
<td>5.38</td>
<td>8.60</td>
<td>5.38</td>
<td>7.53</td>
<td>26.89</td>
</tr>
<tr>
<td>30+ F W-DAY</td>
<td>8.84</td>
<td>9.77</td>
<td>7.44</td>
<td>4.65</td>
<td>30.70</td>
</tr>
</tbody>
</table>

* Sum of the four time points. The expected percentage of total accidents for these time points is 16.68%.
Figure 6.12. Accident frequency distribution by road type.
In general, accidents on main roads were more common between 01.00 to 08.00 and the pattern reversed for the remaining time periods. Both road types showed bi-modal accident distributions with a higher early morning peak (04.00 - main roads, 03.00 - unclassified roads) and a smaller afternoon accident peak (15.00 - main roads, 17.00 - unclassified roads).

Insert table 6.7

6.9 Discussion

The difficulties in demonstrating the effect of sleepiness in industrial studies at night has led to the use of alternative data sets. The study of SVA provides a good base because it describes: (a) a task which is predominantly self paced, (b) a vast database in which meaningful accidents are recorded by time of day, and (c) the database allows other possible explanations to be excluded. Meeting these conditions, provides some confidence for inferring the effect of sleepiness, when the resulting time of day performance variability approximates the timing of the sleepiness rhythm.

The results clearly found a relationship between the timing of the sleepiness rhythm and performance variability, such that accidents were highest in the early morning (03.00), with a secondary peak at 14.00. When these data were adjusted for traffic density, the results were similar to recent English findings (Horne & Reyner, 1995b). The ability to largely replicate findings across international settings, provides further support for the effect of a sleepiness rhythm. However, because this study used a similar methodology to Horne and Reyner, the existence of a common artefact influencing both results cannot be discounted.

A second aim of this study was to find an alternative method to traffic density with which to adjust the accident frequency. Traffic density was criticised on conceptual
Table 6.7
Accident Distribution between 02.00 and 06.00 on Main and Unclassified Roads by Driver Characteristics

<table>
<thead>
<tr>
<th></th>
<th>Drivers under 30 years</th>
<th>Drivers 30 years and over</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Males</td>
<td>Females</td>
</tr>
<tr>
<td></td>
<td>W-END</td>
<td>W-DAY</td>
</tr>
<tr>
<td>Time</td>
<td>Main</td>
<td>Uclass</td>
</tr>
<tr>
<td>02.00</td>
<td>30</td>
<td>16</td>
</tr>
<tr>
<td>03.00</td>
<td>39</td>
<td>26</td>
</tr>
<tr>
<td>04.00</td>
<td>39</td>
<td>24</td>
</tr>
<tr>
<td>05.00</td>
<td>33</td>
<td>21</td>
</tr>
<tr>
<td>06.00</td>
<td>21</td>
<td>14</td>
</tr>
<tr>
<td>Total</td>
<td>162</td>
<td>101</td>
</tr>
<tr>
<td></td>
<td>49</td>
<td>26</td>
</tr>
</tbody>
</table>

Key: W-END = Weekend; W-DAY = Weekday; Main = main roads; Uclass = unclassified roads.
and methodological grounds.

There is ample evidence showing road use does indeed vary by time of day, with younger and particularly male drivers experiencing the highest accident rates (Fell, 1994; Pack et al. 1995; Summala & Mikkola, 1994). These accidents also show variability by the day of the week (Brorsson et al. 1993; Langlois et al. 1985). The effect of age, gender and day of the week was illustrated in a series of raw plots (see figures 6.3-6.9). These variables were termed ‘driver characteristics’ and it was suggested these may better serve in adjusting accident frequency by time of day than traffic density.

In general, males tended to have more night time accidents and females had more day time accidents, irrespective of age and day of week categories. Females aged <30yo on the W-END showed a similar accident peak to males of the same category. Females also showed a morning and afternoon peak that fluctuated relative to age and day of week categories. It is suggested the morning peak may have a cultural rather than biological explanation. In keeping with Summala and Mikkola (1994), younger drivers had more night time accidents and older drivers had more afternoon accidents.

Despite the various driver characteristics, each showed with varying clarity early morning and/or afternoon accident peaks. This is interpreted to show road use differences and provided further support for adjusting accident frequency by driver characteristics. When the accident frequency was weighted for driver characteristics, the same bi-modal accident probability was found (with the primary peak at 03.00 and the secondary peak at 14.00) as for the traffic density adjustment. However, the adjustment for driver characteristics indicated a higher accident probability at 03.00 than did adjustment by traffic density (0.25 versus 0.21).
Road type was also examined for its role in accident distribution by time of day. In general, accident distribution for both road types produced early morning and afternoon peaks but some differences were noted. Accidents on main roads showed greater variability between early morning and afternoon peaks than did accidents on unclassified roads (see figure 6.12). Furthermore, there were a higher percentage of main road accidents from 01.00 to 09.00. Outside of these times, accidents were higher on unclassified roads. Explanations for these differences are not known. One possibility is that longer distances are travelled on main roads at night. Table 6.7 clearly shows male drivers <30yo during the W-END accounted for the majority of main road accidents during the early morning hours.

The complete data set provided by the RTA (excluding accidents attributable to speeding and drinking) suggested that fatigue accounted for 5.3% of total road vehicle accidents over the five year period. The application of the subsequent 'exclusion' criteria resulted in a sleepiness estimate of 1.12%. This estimate is considerably lower than the 16% reported by Horne and Reyner (1995a). Seeing these two studies used similar criteria to determine sleepiness accidents, this large variance was surprising. Nonetheless, the two independent studies showed a similar timing for sleepiness accidents and perhaps both studies also underestimate the problem since the exclusion method is very conservative. It is likely that sleepiness is also a factor in possibly a greater number of other accidents (Dinges, 1995).

The similar accident timing between the present study and Horne and Reyner (1995a) does not however, result in a similar accident probability. Adjusting the accident rate for traffic density showed the difference between maximum and minimum accident risk to be 22.8 times compared to Horne and Reyner's 49.8. The major reason for this variance would be differences in traffic density between the two studies. Furthermore,
Horne and Reyner's estimate is compromised by having applied a national traffic estimate to a local accident region.

Accident probability calculated using the driver characteristic method showed the difference between maximum and minimum accident risk was 35.4. It was earlier suggested that this is a purer measure and suggests traffic density underestimates accident risk. Future studies are encouraged to adopt the driver characteristic method for adjusting accident data. The use of this method however, makes the assumption that the driver characteristics involved in accidents are in general, a reflection of actual road use. In the absence of road use norms, this assumption is reasonable.

The finding that the early morning accident peak was higher than the afternoon peak was in keeping with the literature (Bjerner et al. 1955; Folkard, 1997; Horne & Reyner, 1995a; Mitler et al. 1988). The smaller afternoon peak appears to be consistent with a reduced sleepiness drive during the afternoon (Dement & Carskadon, 1982; Horne, 1988; Monk, 1991). This reduction appears to be a biological function, that is further dampened by day time stimulation from a number of sources.

In reviewing these findings, it is important to note some limitations. This study utilised a correlational design along with the method of exclusion to identify sleepiness related accidents. Whilst it was considered that as many variables known to be associated with accident causation were removed, it cannot be certain that all variables were removed. For example, journey length (Fell & Black, 1997), journey commencement (Pokorny et al. 1987) and the role of a passenger may also cause an accident. This highlights a general limitation of arguing that a circadian rhythm of sleepiness is present in field data when it is not possible to experimentally control or statistically correct for all possible other causes. It is a limitation that applies to all correlational studies and prevents causal statements being offered.
Finally, this study used accidents from three urban areas but the traffic density estimates were based on those in Sydney (the largest of the cities). The two smaller cities do not carry the same level of traffic volume but they have a similar timing for 'rush hour'. It would have been better to review the accidents and traffic density in the three cities separately but traffic density estimates were not available for the smaller cities.

This study found a clear relationship between the timing of the sleepiness rhythm across the day and the pattern for accident distribution in SVA. Accidents peaked during the early morning and showed a smaller secondary peak in the afternoon hours. The accident rate was also shown to be influenced by age, gender and day of the week. It was argued that adjusting accident rates by driver characteristics may provide a better measure for examining the effect of sleepiness. Indeed, this method suggested that adjustments made using traffic density underestimate accident risk. Although these findings were obtained from a correlational design, these findings corroborate the findings from similar studies. Furthermore, the results are also in line with those found in prospective experimental designs (Kecklund & Akerstedt, 1993; Lenne et al. 1997) and EEG studies (Torsvall & Akerstedt, 1987).