Forecasting Pavement Surface Temperature Using Time Series and Artificial Neural Networks

by

Behzad Hashemloo

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AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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I understand that my thesis may be made electronically available to the public.

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Abstract

Transportation networks play a significant role in the economy of Canadians during winter seasons; thus, maintaining a safe and economic flow of traffic on Canadian roads is crucial. Winter contaminants such as freezing rain, snow, and ice cause reduced friction between vehicle tires and pavement and thus increased accident-risk and decreased road capacity. The formation of ice and frost caused by snowfall and wind chill makes driving a very difficult task. Pavement surface temperature is an important indicator for road authorities when they are deciding the optimal time to apply anti-icer/deicer chemicals and when estimating their effect and the optimal amounts to apply. By forecasting pavement temperature, maintenance crews can figure out road surface conditions ahead of time and start their operations in a timely manner, thereby reducing salt use and increasing the safety and security of road users by eliminating accidents caused by slipperiness.

This research investigates the feasibility of applying simple statistical models for forecasting road surface temperatures at locations where RWIS data are available. Two commonly used modeling techniques were considered: time-series analysis and artificial neural networks (ANN). A data set from an RWIS station is used for model calibration and validation. The analysis indicates that multi-variable SARIMA is the most competitive technique and has the lowest number of forecasting errors.

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Chapter 1
Introduction

1.1 Winter Weather and Winter Maintenance Operation

Transportation networks play a very significant role in the economy and safety of Canadians. According to Transport Canada's annual report (2006), the road network in Canada consists of more than one million two-lane equivalent kilometers. In 2006, commercial transportation industries in Canada accounted for \$45.8 billion. Trucking was the most important industry, making up \$15.1 billion, or 1.4 per cent of the total Gross Domestic Product (GDP). Urban transit accounted for \$3.2 billion, or 0.3 per cent of GDP. Provincial, territorial, and local governments spent almost \$20.8 billion on transportation networks during the 2005/06 winter season, 10.8 per cent more than during the 2004/05 period. In 2005/06, total government spending on roads increased 11.9 per cent to \$17.4 billion, compared to a 7.9 percent increase in 2004/05. The country's road budget accounts for 72 percent of its overall spending on transportation. Road expenditures have risen progressively, at an average annual rate of 5.8 per cent for the past five years. A 2006 report showed a slight (0.4 percent) increase in casualty collisions in 2005 (the most recent statistics) compared to 2004. There were 2,925 road user fatalities in 2005, a 7.3 percent increase over the 2004 total of 2,725. Thus, improving safety on Canadian roads is critical.

During the winter season, most Canadian regions are subject to adverse weather conditions. The severity of winter weather varies across the country. For instance, Ontario experiences a total snowfall accumulation ranging from 115 to 426 centimeters and 17 to 74 days with a wind chill temperature of less than -20°C (Environment Canada Online Archive). Except for the west coast, most regions in Canada have winter climatic conditions similar to Ontario's. The formation of ice and frost caused by snowfall and wind chill makes driving a very difficult task. Icy conditions may be compounded by freezing rain, and strong winds, and the accumulation of precipitation on road surfaces. According to an Environment Canada report, winter weather traffic accidents kill more than 100 people in Canada each year--more than the number of Canadians killed by other weather-related accidents such as tornadoes, thunderstorms, lightening, floods, and hurricanes.

Winter phenomena such as freezing rain, snow, and ice cause reduced friction between vehicle tires and pavement and thus increased accident-risk and decreased road capacity. An analysis by Knapp (2002) indicates that a winter storm generally decreases traffic volume by approximately 29 percent, with a range of 16 to 47 percent, depending on location and severity of the storm. As well, a statistical analysis of collected data indicates that vehicle speed is significantly lower during poor weather conditions, a finding that confirms a positive relationship between the number of storm events and traffic volume reduction for a 95 percent confidence interval. The research indicates that the number of winter-related accidents depends largely on trip distance, storm duration, and number of snow falls (Knapp, 2002). According to the Highway Capacity Manual (FHWA 2000), rain can cause a reduction in free flow speed of between 13 to 16 km/h on a road with a capacity of around 2400 veh/h, depending on how heavily it rains.

For snow, the reduction was found to be greater. One of the issues related to snow is that snow covers lane markings, thereby leading most drivers to seek greater lateral clearance as well as longer headways. For example, a three-lane freeway segment is used as two widely separated lanes. Research shows an average of 64.5 km/h reduction in free-flow speed and a 30 percent drop in capacity in an urban area during heavy snow (Knapp, 2002). Ice and snow can increase the risk of accidents by up to several orders of magnitude. A study carried out by Andrey et al. (2003) reveals that a 75 percent increase in traffic collisions and a 45 percent increase in weather-related injuries are associated with precipitation. The results from another study demonstrate that the highest accident risk was linked to road slipperiness caused by rain or sleet on a frozen road surface (Norrman et al., 2000). To keep highways in safe and efficient condition, transportation authorities spend a lot of resources every year on snow and ice control. In Canada, the average annual expenditure on winter road maintenance exceeds $1 billion, and includes application of over 500 million tons of salts – a significant environment concern.

In order for road conditions to be safe and efficient, bare pavement must be maintained. The term winter maintenance is defined as a group of activities to keep roads clean and safe for users. For transportation agencies mechanical, chemical, and thermal methods are generally available. Mechanical operations include sand spreading and snow plowing, which are usually performed on a regular basis in almost all rural and urban regions with frozen precipitation or significant snowfall (Perrier et al., 2006). Chemical methods are generally used for deicing and anti-icing purposes or, more specifically, to melt ice already formed on pavement surface, or to prevent formation of ice through freezing point depressants. Thermal techniques involve applying heat to the roadway surface in order to remove snow and ice or to prevent them from bonding to pavement. The type and amount of anti-icer/deicer consumption depends upon pavement surface temperatures and winter road surface conditions.

Pavement surface temperature is an important indicator for road authorities when they are deciding the optimal time to apply anti-icer/deicer chemicals (Minsk, 1998). In addition, road temperature is necessary in estimations of the effect of a particular deicer and the optimal amount required (Pilli-Sihvola et al., 1993). By forecasting pavement temperature, maintenance crews can figure out road surface conditions ahead of time and start their operation in a timely manner, thereby increasing the safety and security of road users by eliminating accidents caused by slipperiness.

1.2 Spatial and Temporal Mapping of Pavement Temperature

The goal of winter maintenance is to make sure the transportation network is kept safe and clear of winter contaminants by applying the right treatment in the right place at right time and at minimum cost. Pavement temperature is therefore a crucial factor in determining the effectiveness of winter maintenance operations to keep roads safe. Accurate and timely information about pavement temperature helps road managers to apply winter maintenance methods such as salting effectively in regards to salting time and amount. Pavement temperature differs based on weather conditions and road location. Since weather and temperature conditions change with time of day and location along a route, being able to predict pavement temperature along individual maintenance routes is useful.

As a part of integrated winter maintenance operations, thermal mapping techniques, which use infrared equipment to measure road surface temperature in a road network, play an important role in monitoring real-time road surface temperatures. In the 1980s, a thermal mapping technique was developed in Europe wherein an infrared thermometer was mounted on a vehicle to measure surface temperature and to display the variation of surface temperature along each route in the form of a graphical diagram showing surface temperature against distance (Gustavsson et al., 1988). To explore possible relationships between road surface temperature and topography-one of the most important factors controlling the variation of surface temperature- a step-wise regression technique was proposed to find out possible statistical relationships between road temperature and altitude on different surveyed routes (Shao et al., 1997). This research deduced that thermal mapping is an effective method to show the spatial variation of road surface temperature by providing a dynamic picture of spatial and thermal road temperature variations.

1.3 Problem Definition

Winter contaminants and ice formation present significant potential obstacles to travel safety by reducing the friction between tires and road surface. As a result, vehicle collision risk increases considerably and can cause significant costs to society, the economy and the environment in terms of property damage, personal injury, and underground water pollution.

To control adverse effects of winter weather and ice formation on pavement surface, road network authorities undertake winter maintenance operations. Monitoring of winter road surface conditions is mostly done through personal observations and manual recordings, which are time consuming and limited in reliability and details, especially for remote areas where adverse weather makes the road condition more serious. In a road network, there are critical spots that are susceptible to black ice, glazing, or frost and where winter maintenance is most critically needed during and after each storm. Even in urban areas, some limitations in geometrical and topological characteristics make it difficult to maintain safe conditions during a winter season. The salt use in these operations is costly and has negative impacts on the environment; therefore, its use should be kept to a minimum. Forecasting surface temperature is one of the most important factors in applying a cost-effective and efficient winter maintenance operation.

Most cities and provinces in Canada, including Ontario, have installed Road Weather Information Systems (RWIS) to help manage their winter maintenance operations by recording weather and pavement data. However, RWIS technology suffers from many shortcomings and is limited in spatial and temporal coverage, which limits its applicability for this purpose. Therefore, a valuable cost effective option is to use RWIS data to develop statistical models that are capable of forecasting pavement surface temperature at different locations with similar weather and road surface conditions. These models should be accurate, simple, reliable, and efficient to maintain and develop.

In the literature, there are a number of models for predicting pavement temperature; however, most of them were developed to estimate the highest or lowest surface temperature using meteorological variables such as air temperature, dew point, and wind speed. Some were developed based on heat transfer equilibrium theories. All these models require a large number of variables, with complex equations and significant amounts of data to maintain.

1.4 Research Goals and Objectives

The objective of this research is to investigate the feasibility of applying simple statistical models to forecast road surface temperature at locations where RWIS data are available. This research specifically has the following objectives:

- To conduct a literature review on winter maintenance operations and methods and road surface temperature forecasting models,
- To develop methods and models that can be used to forecast road surface temperature using historical and real-time observations of weather and road surface conditions, including time-series analysis and Artificial Neural Networks (ANN),
- To perform a comparative analysis of models to identify the most accurate one in regards to minimum error factors.

This research describes the data set used for model calibration and testing and the details of the model calibration and validation processes. The major findings on the comparative performance of these models are highlighted.

1.5 Organization of Thesis

This thesis is comprised of five chapters and a series of appendices to support the text. Chapter 1 introduces the background, problem definition, objectives, and goals of the research. A detailed literature review is provided in Chapter 2 to summarize the state of the art on road surface temperature estimation and forecasting. Chapter 3 describes the field experiment study site and data sources used in the analysis. Chapter 4 explains the steps and the results of comparative analysis conducted in this research. Results from the statistical modeling of road surface temperatures are described in this chapter. Chapter 5 summarizes major findings, and suggests recommendations for future research. Appendices follow to provide all input data used in this thesis.

Chapter 2
Literature Review

Road surface temperature determines whether or not a layer of water on pavement will freeze or falling snow will melt away during snowy days. When road surface temperature drops rapidly (e.g., quicker than the air temperature), a dangerous layer of frost may form on the pavement surface (Karlsson, 2001). Because weather and road temperature vary with time and location, winter maintenance methods are most effective when road authorities receive information about current and future pavement temperature and select appropriate deicer/anti-icer for particular locations. As discussed in Chapter 1, the primary objective of this research is to develop and evaluate alternative models that can be used to make real-time, short-term forecasting of pavement temperatures at specific highway locations.

Forecasting of pavement temperature is, however, a challenging task. Pavement temperature is affected by a large number of climatic and topological factors that vary over space and time with significant uncertainties. Furthermore, various data sources such RWIS and weather forecasts are limited in spatial and temporal coverage (Chapman et al., 2001, and Thornes et al., 2005). Wind speed, air temperature, and humidity have been identified as the major factors by several researchers (Scherm, 1993 and Gocheva, 1990). In addition, dew point, precipitation, and surface condition (i.e., wet, dry, or snowy) also have an effect on pavement temperature. This chapter first discusses winter maintenance operations methods and the dependency of these methods on road surface temperature. It then provides a general description of mapping pavement temperature, followed by a section on the factors affecting pavement temperature. Then variation in the pavement temperature cycle is discussed. This chapter ends with an in-depth review of past efforts at applying, modeling, and forecasting of pavement temperatures for winter road maintenance operations.

2.1 Winter Maintenance Operations Methods

Winter road maintenance operations are a group of activities to keep roads clean and safe for users. The most common snow and ice control techniques available for a transportation agency are generally mechanical and chemical methods. Mechanical techniques include sand and salt spreading and snow plowing and removal; chemical methods include application of chemicals as freezing point depressants. Chemical techniques are generally used for deicing and anti-icing purposes or, more specifically, to melt ice already formed on the pavement surface, to prevent formation of ice, and prevent the build-up of compacted snow tightly bonded to the pavement. Road surface temperature is often one of the most important factors for determining which maintenance operations are most suitable and applicable under a given condition. The following section provides an overview of these techniques and their relation to road surface temperature.

2.1.1 Mechanical Methods

Mechanical removal methods are strategies that involve the actual physical removal of an accumulation of snow or ice by means of plowing, sweeping, gritting, or blowing, without the application of chemicals. Spreading and plowing operations are usually performed on a regular basis in almost all rural and urban regions experiencing frozen precipitation or significant snowfall. However, in urban areas with large snowfalls and extended subfreezing temperatures, the large volumes of snow plowed from roadways and walkways generally exceed the available space along roads for snow storage, and therefore must be disposed of by some means. The most common solution is to load snow into trucks for transport to disposal sites. On the other hand, in rural regions, snow is often simply pushed to the sides of roadways without being removed and hauled (Perrier et al., 2006). These strategies are suitable for use in different situations. For example, for low Level Of Service (LOS) routes or unpaved roads, they could be very efficient and sometimes the only solution. If pavement temperature is higher than freezing point and snow has not bonded to the pavement yet, these methods are effective (NCHRP).

Echelon plowing is the practice of staggered snowplows operating across all lanes of a roadway. Though sometimes annoying to drivers, it is often the safest and most efficient snow removal method for multi-lane highways. Plowing in echelon clears all lanes at once by passing a ridge of snow from one plow to the next. To do the job right, snowplows and salt and sand trucks must travel more slowly than regular traffic. Sight lines and visibility near any working snowplow are severely restricted by blowing snow, and passing, either between or around these snowplows, is extremely dangerous because of whiteout conditions and the ridge of snow being passed between plows.

Sanding (dispersing sand on the road surface) is another method common winter maintenance operation. Sand is useful to provide traction on slippery surfaces; however, it does not melt snow and ice. Sand is used most often when temperatures are too low for salt to be effective, for example, when temperatures fall lower than -12° C and bare pavement becomes hard to achieve (MTO report, 2005). Sand is also used at higher temperatures if traction is required immediately, particularly on hills, curves, bridges, intersections, and on snow-packed roads.

2.1.2 Chemical Methods

Chemical methods are those using chemicals as freezing point depressants to melt ice already formed on the pavement surface, to prevent formation of ice, or to prevent the build-up of compacted snow tightly bonded to the pavement. The most common chemicals are sodium chloride (NaCl), calcium chloride ($CaCl_2$), calcium magnesium acetate (CMA), magnesium chloride ($MgCl_2$), potassium acetate (KAc), and Urea (Ketcham et al., 1996 and Minsk, 1998). Different chemicals have different ranges of temperatures under which they are most effective.

Table 2.1 shows the lowest effective temperatures and eutectic temperatures for these six commonly used chemicals. A eutectic or eutectic mixture is a mixture at such proportions that the melting point is as low as possible, and the temperature at which melting takes place is called the eutectic point. The eutectic temperature is used to guide the selection of chemical agent. The table shows that the lowest effective temperature used in winter maintenance operations is substantially higher than the eutectic temperature for all of the chemical agents.

Table 2.1: Lowest Effective Temperature for Different Chemicals Compared to the Eutectic Temperature (Source: Data Obtained from Minsk, 1998 and Ketcham et al., 1996)

Chemical	Lowest Effective Temperature (°C)	Eutectic Temperature (°C)	Eutectic Concentration (%)
Calcium chloride (CaCl2)	-29	-51	29.8
Calcium magnesium acetate (CMA)	-7	-27.5	32.5
Magnesium chloride (MgCl2)	-23	-33	21.6
Potassium acetate (KAc)	-25	-60	50
Sodium chloride (NaCl)	-7	-21	23.3
Urea	-4	-11.7	32.6

Note: The solution concentration is similar for both temperatures

Chemical methods can be divided into two main groups: de-icers and anti-icers. De-icing operations involve breaking the bond between pavement and frost on the road surface. Although effective, de-icing operations are not always efficient. A lack of reliable site-specific weather forecasts results in many highway agencies having to wait until a storm hits before sending out their maintenance crews to start the operation. By then, snow or frost is already bonded to the pavement and difficult to remove.

Anti-icing is a relatively new strategy for preventing a strong bond from forming between snow or frost and the pavement surface. It involves applying a chemical in advance to lower the temperature at which freezing takes place. If snow can be prevented from bonding to the pavement, the roadway will remain wet or slushy, rather than icy. Motorists will be better able to control their vehicles, thus making traveling safer (Mergenmeier, 1995). For this reason, salt is often spread early in a storm to prevent snow build-up and to aid in snow removal operations. Salt should not be applied to the road surface when the pavement temperature is +2 or rising, and in most circumstances, salt should be applied after the road has been plowed. According to the Region of Waterloo's Winter Maintenance Policy, salt ought to be applied at the centre lanes, and the application rate should be in accordance with Table 2.2.

Table 2.2: The Salt Application Rate (Source: Winter Maintenance Policy, Region of Waterloo)

Class	Salt Application (Pavement Temperature higher than -5°C)	Salt Application (Pavement Temperature -5°C to -12°C)	Prewetted Salt Application (Pavement Temperature higher than -5°C)	Prewetted Salt Application (Pavement Temperature -5°C to -12°C)
1	125 kg/2-lane km	141 kg/2-lane km	100 kg/2-lane km 25 L/2-lane km	113 kg/2-lane km 28 L/2-lane km
2	125 kg/2-lane km	141 kg/2-lane km	100 kg/2-lane km 25 L/2-lane km	113 kg/2-lane km 28 L/2-lane km
3	125 kg/2-lane km	141 kg/2-lane km	100 kg/2-lane km 25 L/2-lane km	113 kg/2-lane km 28 L/2-lane km
4	100 kg/2-lane km	125 kg/2-lane km	80 kg/2-lane km 20 L/2-lane km	100 kg/2-lane km 25 L/2-lane km
5	100 kg/2-lane km	125 kg/2-lane km	80 kg/2-lane km 25 L/2-lane km	100 kg/2-lane km 25 L/2-lane km

It might be noticed that salt is often applied in a narrow strip along the centre or high point of the highway. This practice provides a salt-water mixture that flows across the roadway, ensuring the most efficient and effective use of the material. Although chemical agents are the most efficient materials for winter maintenance, they may damage the environment and infrastructure by their negative effects (Burtwell, 2001; Ketcham et al., 1996; Minsk, 1998). Thus, alternative methods such as pre-wetting of dry salt, Direct Liquid Application (DLA), and Fixed Automated Spray Technology (FAST) have been anticipated to optimize the quantity of chemicals used.

2.1.2.1 Pre-wetting of Dry Salt Technique

Pre-wetting is a process of covering salt aggregates with liquid before dispersal onto the road surface. This initial addition of liquid makes salt particles start to dissolve and reduces the time-lag between application and activation of the salt. As well, this amount of liquid prevents salt aggregates being displaced from the pavement surface by either wind or traffic flow before they start to dissolve. Pre-wetting can be used for both anti-icing and deicing purposes. For de-icing, the mixture is usually applied after the road is plowed. For anti-icing applications, pre-wetted salt is applied in the early stage of a storm to prevent bonding action. This technique is more efficient than applying solid salt alone because it minimizes salt use by providing primary liquid to begin the salt solution and ensures that the salt adheres to the road surface (Blackburn et al., 2004; Burtwell, 2001; Minsk, 1998; and Ketcham et al., 1996).

2.1.2.2 Direct Liquid Application (DLA)

Direct Liquid Application means that liquid chemicals are applied directly on the road surface. In this technique, a chemical agent is used in advance of any storm event to prevent formation of bonds between snow and pavement surface. The common chemicals used for DLA are calcium chloride, magnesium chloride, sodium chloride, potassium acetate, and calcium magnesium acetate. To minimize corrosion, a corrosion inhibitor is usually added to calcium chloride, potassium acetate, and magnesium chloride. There is specialized equipment capable of applying liquid agents uniformly at different speeds from 10 to 70 kilometers per hour at a spreading width of 2 to 8 meters (Fonnesbech, 2004; Minsk, 1998; Ketcham et al., 1996; Blackburn et al., 2004).

2.1.2.3 Fixed Automated Spray Technology

A relatively new system called Fixed Automated Spray Technology (FAST) has been in service in North America for several years. This technology automatically detects weather and road conditions and applies anti-icing liquids in advance of frost and ice creation on the road surface by means of an equipment system. A FAST system consists of three subsystems: sensors for detecting road weather and surface conditions, a hydraulic and spraying system, and a control system. Figure 2.1 shows a FAST nozzle spraying anti-icer in a Hwy. 401/404 HOV lane tunnel in Toronto during winter 2007.

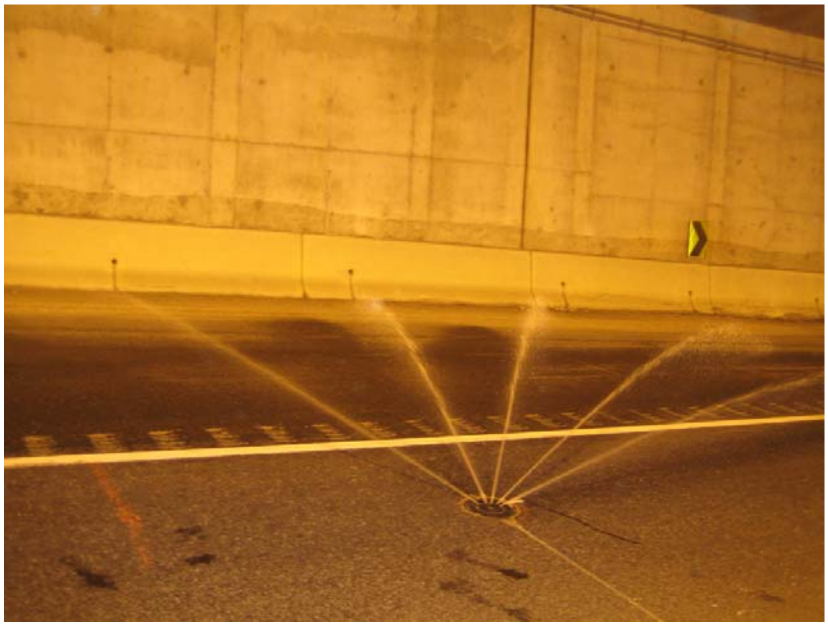

Figure 2.1: Fixed Automated Spray Technology (FAST) Nozzle in a Hwy. 401/404 HOV Tunnel

There are three critical reasons to install a FAST system. The first is safety, particularly at spots prone to frost accidents; deploying a FAST system can provide application of chemicals to control ice and frost in a timely and appropriate manner. The second is to allow quick action during storm or frost conditions at a structure or particular section of highway that is very remote from the location where trucks load chemicals or abrasives. The third is to ensure the delivery of anti-icing chemicals regardless of traffic conditions; locations with high traffic volume and those spots subjected to adverse winter weather often suffer from traffic jams, causing significant obstacles to plowing and salting trucks that are operating to control icy conditions, thus making the level of congestion much worse. Using a FAST system ensures the delivery of anti-icing chemicals regardless of traffic conditions. These reasons can be summarized as safety concerns during adverse weather, remoteness of location, and significant volume of traffic in critical spots that suffer from frost conditions (Bell et al., 2006).

Generally, the FAST system is composed of an anti-icing fluid container, a pump, and a network of spray nozzles capable of dispersing liquid anti-icing agent on the road surface. A Programmable Logic Controller (PLC) provides the sequencing and duration of spray for each spray nozzle (Roosevelt, 2004). In addition, a FAST system includes a number of weather and surface temperature sensors, together with a computer that has an algorithm to determine when frost conditions have occurred and when liquids need to be sprayed (Bell et al., 2006). Road surface temperature, current and forecasted, is a critical input to the spraying control logic of a FAST system.

2.2 General Description of Mapping Pavement Temperature

As discussed previously, pavement temperature has a crucial effect on various winter maintenance operations methods. Accurate and timely information about pavement temperature helps road managers to select the most effective maintenance techniques. Pavement temperature is commonly collected by RWIS and infra-red thermometers (IR) installed on patrol vehicles or maintenance trucks. These technologies, however, have limitations. For example, RWIS provides only point measurements at fixed locations along a maintenance route, and lacks spatial coverage. Temperature measurements by maintenance vehicles equipped with IR provide only a few snapshots of pavement temperature over a snow storm, short of temporal coverage. Pavement temperature differs by weather condition and location. To ensure that the right maintenance treatments are delivered to the right place at the right time, it is necessary to determine the variation patterns of pavement temperature both over time (temporal mapping) and over individual route segments (spatial mapping). Spatial and temporal mapping of road surface temperatures are collectively called thermal mapping.

The most basic form of thermal mapping was developed in Europe in the 1980s. An infrared thermometer was mounted on a vehicle to measure surface temperature and to display the variation of surface temperature along each route in the form of a graphical diagram showing surface temperature against distance (Gustavsson et al., 1988). To explore possible relationships between road surface temperature and topography, as this was felt to be one of the most important factors controlling the variation of surface temperature, Shao (1997) applied a step-wise regression technique to find out possible statistical relationships between the surface temperature of a route and the altitude of the route. This research shows that thermal mapping is an effective method to demonstrate spatial variation of road surface temperature by providing a dynamic picture of spatial and thermal variations of road temperature (Shao et al., 1997).

2.3 Factors Affecting Pavement Temperature

There are many factors affecting road surface temperature, which can be classified into permanent and non-permanent ones. Topographical features (slopes, valleys, adjacent lakes, mountains, and woods), geographical coordination (altitude, latitude, and longitude), and road structure (material, thickness, and layers combination) are called permanent factors because they have a constant effect on surface temperature, and their influence is almost fixed during the winter season. In contrast, traffic and weather conditions can be considered non-permanent factors since their changes depend on time and location. Table 2.3 shows these factors and their possible effects on pavement temperature (Shao, 2000).

Table 2.3: Variables Controlling Surface Temperature and Their Significance (Shao, 2000)

Parameters	Effects on Road Surface Temperature
Latitude	Important, because it determines average thermal status or temperature in winter
Longitude	Little impact
Urban	Minor to moderate
Topography	Almost constant, since it varies locally and depends on scale and pattern of the topographical features and weather conditions
Road Construction	Minor influence
Traffic	Generally small, but could be large under heavy traffic and during rush hours
Weather	The most significant parameter

Topography varies locally, and the effect is almost constant depending on the pattern and scale of the topographical features and weather conditions. The latitude of the maintenance route is another important factor determining the overall climatic nature of the route. Traffic generally has little effect on road temperature except during under heavy traffic and rush hours. Since traffic has fewer effects on road temperature, weather condition will remain the only non-constant significant factor influencing road temperature (Shao, 2000).

2.4 Cyclic Variation of Pavement Temperature

Pavement temperature generally follows the trend of air temperature, with a cyclic daily variation pattern. Knowledge of this cyclic temperature trend is important in forecasting and modeling surface temperature. In the literature, several researchers have investigated the trends of road temperature during daily cooling and warming cycles using data from different locations with different weather characteristics. Kallas (1966) conducted a study to determine road temperature trends from yearly data on a test section at College Park, Maryland. Pavement temperature was measured at the surface and at different depths in addition to air temperature for comparison. The study concluded that cycles of hourly temperature of pavement and air reach minimum before sunrise and increase during day time to a maximum in early afternoon around 3:00 pm. In another study, Straub et al. (1968) measured surface temperatures during one year at five-minute intervals. The test section was located at Potsdam, N.Y., at Clarkson College. Air temperature, amount of solar radiation, and cloud cover percentage were also recorded in addition to surface temperature. This research shows that air and surface temperature follow a sine wave pattern where the minimum temperature occurs in the early morning and the maximum temperature happens in the early afternoon. The study confirms that air temperature is one of the major factors that has a direct relation with pavement temperature.

Empirical monographs were developed by Rumney and Jimenez (1971) from yearly data at a test section in Tucson, Arizona, to predict road surface temperature as a function of air temperature and hourly-based solar radiation. Their results were similar to those of previous researchers, in that road temperature reaches its minimum in early morning before sunrise and increases rapidly as solar radiation heats up the road surface to its maximum temperature between 12:00 to 3:00 pm. In addition, this study concludes that road surface temperature at night depends on the atmospheric conditions and stays above the air temperature in summer and may fall below the air temperature in winter.

Bosscher et al. (1998) monitored the thermal behavior of pavement as affected by weather in their research by installing field instrumentation in two of their test sections. The instruments were used to monitor pavement temperature as a function of time and depth from the surface. Pavement temperature and weather data, including air temperature, were collected during the first 22 months of the test period. Their typical graph of recorded temperature (Figure 2.2) shows that pavement temperature follows air temperature, and at all depths, pavement temperature generally is higher than air temperature, particularly during the night. However, sometimes during cloudy days, pavement temperature was lower than air temperature. At night, when the air temperature reaches its minimum, pavement experiences its lowest temperature, and the deepest layer has the warmest temperature. Figure 2-2 suggests that the minimum pavement temperature is higher than the minimum air temperature constantly. However, when the air temperature rises to its maximum during the day, the surface layer experiences the highest temperature, and the bottom layer is the coldest. Because of solar radiation, the maximum road surface temperature is usually higher than the maximum air temperature. The research concludes that during each day, the pavement temperature trend reverses two times, generally at sunrise and sunset.

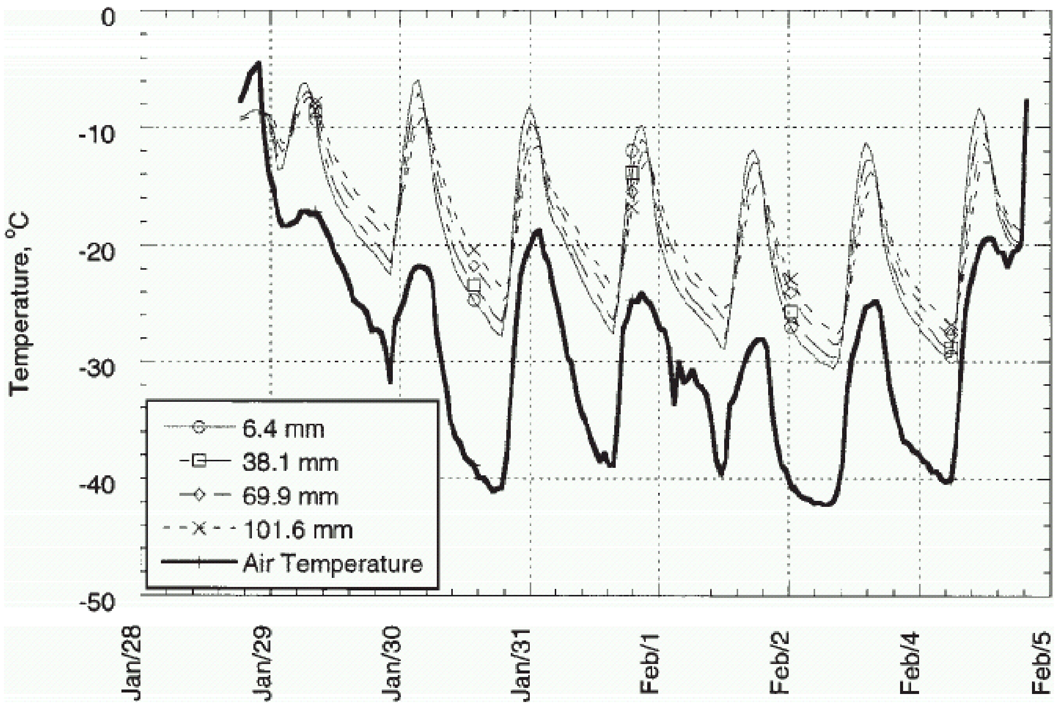

Figure 2.2: Pavement and air temperature profile over time (Source: Bosscher et al., 1998)

Previous trend analysis recognized that although the highest and lowest temperature at specific periods could change yearly, pavement and air temperatures follow a similar pattern each year. This finding suggests that one year of data might be sufficient to capture the general trends of air and pavement temperatures.

2.5 Modeling Pavement Surface Temperature

Many studies have been conducted in the past to model pavement temperature with different application perspectives and goals. Some of these models use simple meteorological factors such as air temperature and humidity for forecasting, while others involve higher levels of complexity based on solar radiation and heat flow rate. Based on the forecasting objectives, the factors included in these models may vary. Linear regression is one of the primary methods that have been used by several researchers to develop forecasting models.

Pavement temperature forecasting models have also been developed as part of the Long-Term Pavement Performance (LTPP) program. The original LTPP program was established by the Strategic Highway Research Program (SHRP) in 1987 to study the long-term performance of in-service pavement. The SHRP-LTPP program included two main areas, General Pavement Studies (GPS) and Specific Pavement Studies (SPS). In 1992, the LTPP program continued under the management of the Federal Highway Administration (FHWA). The LTPP researchers recognized the importance of environmental impact on pavement performance and launched the Seasonal Monitoring Program (SMP) as an integral part of the LTPP program. The primary objective of the SMP was to study the impacts of temporal variations in pavement response and material property due to the separate and combined effects of temperature, moisture, and frost/thaw variations (Rada et al., 1994). This effort has resulted in several pavement temperature forecasting models, which are reviewed in the following section.

Heat Transfer Theories (HTT) was another method used by researchers to create pavement forecasting models. The HTT models are very complex because they require many variables to be estimated and many equations to be calibrated, and thus are exacting to develop and maintain. The following section discusses these methods.

2.5.1 Linear Regression Method in Forecasting Pavement Temperature

Bosscher et al. (1998) were among the first to apply statistical regression techniques to model pavement temperature as a function of air temperature and other meteorological factors. The analysis was focused on developing statistical models to estimate low and high pavement temperatures from meteorological data. The models were compared to the Superpave recommended models and those created by the Long-Term Pavement Performance (LTPP) program. Data on pavement temperature, air temperature, solar radiation, and other meteorological parameters were collected once every hour. Linear regression analysis was used to establish the model to define the minimum pavement temperature as a function of minimum air temperature and other weather parameters. Among several mathematical models, a bilinear model was found to be the best low-temperature model, one for minimum air temperature below 0ºC and the other for minimum air temperature above 0ºC (Bosscher et al., 1998). Although the R^2 value was high at 96.3%, the standard error was also relatively high (2.71°C). The model was improved by adding the average air temperature as a predictor, calculated during the 24-hours preceding the time at which the minimum pavement temperature occurred. The results show that limiting the model to -5ºC results in a better prediction. A similar analysis was conducted applying bilinear regression to estimate maximum pavement temperature using maximum air temperature and daily solar radiation intensity. 10ºC was the cut-off between the two estimated equations.

Other research was conducted by Raad et al. (1998) to model pavement temperature during winter. The research established a correlation between minimum pavement temperature and air temperature for the Alaskan climate. Four climatic zones were considered with different characteristics in regards to temperature variation, humidity level, precipitation, and other climatic parameters. A linear regression equation was fitted for each zone. The results conclude that minimum pavement temperature is always higher than minimum air temperature by 2ºC to 7ºC, depending on the climate zone.

Recently, another set of regression models was developed by Sherif and Hassan (2004). A step-wise regression analysis was applied to predict pavement temperature by using air temperature, dew point, relative humidity, wind speed, wind gust, and wind direction. The study used data recorded from six RWIS stations in the City of Ottawa for the 2001-2002 winter season. Six models were established for each station, and one model was selected for use in the Ottawa area, called the Ottawa-wide model. The study shows that air temperature and dew point as independent variables are the most significant parameters in terms of the model's goodness of fit and P-value. The regression model was further improved by the inclusion of two additional parameters, namely surface temperatures at one hour and two hours in advance. The final model for Ottawa–wide is (Equation 2-1):

$$T_p = 0.12 * T_a - 0.022 * D_p + 1.721 * TLDV_1 - 0.851 * TLVD_2 + 0.096 * C \qquad (2\text{-}1)$$

where,

Tp	=	Current pavement temperature, °C,
Ta	=	Current air temperature, °C,
Dp	=	Current dew point, °C;
TLDV1	=	Pavement temperature one hour before estimation time, °C,
TLDV2	=	Pavement temperature two hours before estimation time, °C,
C	=	Constant value.

This model suggests that the current pavement temperature greatly depends on recent pavement temperatures on previous one-hour and two-hour records.

Unlike Sherif and Hassan (2004), neither Bosscher et al. (1998) nor Raad et al. (1998) attempted to examine any of the problems associated with linear regression techniques such as multicollinearity and autocorrelation. In Sherif and Hassan's study, two time-lag-dependent variables were added to reduce the autocorrelation between current pavement temperature and earlier ones and the multicollinearity between air temperature and dew point.

2.5.2 Models Developed from Long-Term Pavement Performance program

Three pavement temperature prediction models were developed using data collected as part of the Long-Term Pavement Performance (LTPP) program. These models are based on temperature data monitored from 40 sites located in the US and Canada during the Seasonal Monitoring Program (SMP) of LTPP. The data required to estimate pavement temperature includes time of day, depth below the surface, and the average air temperature of the day before (Lukanen et al., 2000). The first model, named BELLS, is to be used to estimate pavement temperature at different depths of pavement by using 5-day mean air temperature, infrared surface temperature reading, and time of day. The model was valid only for a temperature range of 15°C to 25°C. The second model, namely BELLS2, was adjusted to correct infrared temperature data. Furthermore, the 5-day mean air temperature was replaced by the previous day's average of maximum and minimum air temperature. The third model (Equation 2-2), called BELL3, was adapted for use during regular Falling Weight Deflectometer (FWD) testing:

$$T_d = 0.95 + 0.892 * IR + \{-1.25 + \log_{10}(d)\} * \{-0.448 * IR + 0.621 * T_{(day-1)} + 1.83 * \sin(hr_{18} - 15.5)\} + 0.042 * IR * \sin(hr_{18} - 13.5) \tag{2-2}$$

where,

T_d	=	Pavement temperature at depth d, °C
IR	=	Infrared surface temperature, °C
d	=	Depth at which temperature is to be predicted, mm, (d>=25 mm)
$T_{(day-1)}$	=	Average of air temperature for previous day
sin	=	Sine function on an 18-hr clock system, with 2π radians equal to one 18-hr cycle
hr_{18}	=	Time of day, in 24-hr clock system, but calculated using an 18-hr asphalt concrete temperature rise-fall time cycle. To use the time-hour function correctly, divide the number of hours by 18, multiply by 2π, and apply the sine function in radians.

Two other models were established using LTPP seasonal data to estimate maximum and minimum temperature of pavement. These models relate pavement temperature to air temperature, latitude and depth of pavement (Mohseni and Symons, 1998). The following model calculates the maximum pavement temperature:

$$T_{pav}=54.32+0.78\ T_{air} - 0.0025\ Lat^2 - 15.14\ \log_{10}(H+25) + Z\ (9+0.61\ S_{air}^{\ 2})^{0.5}, \tag{2-3}$$

where,

T_{pav}	=	High AC pavement temperature below surface, °C
T_{air}	=	Maximum air temperature, °C
Lat	=	Latitude of the section, degree
H	=	Depth from surface, mm
S_{air}	=	Standard deviation of the high 7-day mean air temperature, °C
Z	=	A critical value from standard normal distribution table under a given level of confidence, e.g., z = 2.055 for 98% reliability.

Similarly, the model for low pavement temperature is

$$T_{pav} = -1.56 + 0.72\, T_{air} - 0.004\, Lat^2 + 6.26\, \log_{10}(H+25) - Z\,(4.4 + 0.52\, S_{air}{}^2)^{0.5}, \quad (2\text{-}4)$$

where,

T_{pav}	=	Low AC pavement temperature below surface, °C
T_{air}	=	Minimum air temperature, °C
S_{air}	=	Standard deviation of the mean low air temperature, °C
Z	=	A critical value from standard normal distribution table under a given level of confidence, e.g., z = 2.055 for 98% reliability,

The statistical tests show that the R^2 value for the first model is 0.76, and the sum of the squared error is equal to 3.0 for 309 observations. In the second model, the R^2 value is 0.96, with the sum of the squared error equal to 2.1 on 411 observations.

2.5.3 Models Developed Using Heat Transfer Theories

Initially, Barber proposed estimating maximum pavement temperature by applying thermal diffusion theory to a semi-infinite mass (pavement) in touch with air. The research established a relation between pavement temperature and air temperature, wind speed, and solar radiation, as controlled by the thermal characteristics of the pavement. Several equations with a number of variables were used to establish this relationship. The variables involved in the model were pavement temperature, air temperature, daily variation and average air temperature, depth measurement from pavement surface, pavement density, specific heat, solar radiation, solar absorption of surface, conductivity, diffusivity, wind speed, and so forth. The study concludes that "calculations indicate the possibility of roughly correlating surface temperatures with the values reported by the Weather Bureau"; thus it is possible to extrapolate field-observed temperatures to other times and locations. To calculate the exact temperature for a given structure, exact values of its thermal properties and the ambient conditions must be known (Barber, 1957).

Dempsey and Thompson developed a heat transfer model by using finite difference equations technique to study frost development and temperature-dependent effects in pavement. The model was established based on a one-dimension Fourier second order partial differential equation of heat transfer for conductive heat flow (Equation 2-5):

$$\frac{\partial^2 T}{\partial x^2} = \frac{1}{\alpha}\frac{\partial T}{\partial t}, \quad x > 0,\ t > 0, \tag{2-5}$$

where T is the pavement temperature, x is depth, α is thermal diffusivity, and t is time. The estimation of the model required a considerable amount of data on thermal properties of pavement materials, meteorological variables, and weather conditions (Dempsey and Thompson, 1970).

A simplified procedure based on principles of heat transfer was proposed by Shao et al. (1997) to forecast pavement surface temperature. The research used the surface temperature history since the morning previous to testing to predict mid-depth layer temperature of pavement at the time of falling weight deflectometer (FWD) on the testing day. The surface temperature history was determined by using the previous day's maximum air temperature, the minimum air temperature of the testing morning, cloud condition, and surface temperatures measured during FWD tests. The field temperature records from several pavement sections provided values of pavement thermal parameters and coefficients in temperature functions that are required in the prediction procedure (Shao et al. 1997). The estimation of the model required significant amounts of data and the solution of mathematically complex differential and integral equations. The solution of the differential equation was given as an integral equation of pavement temperature as a function of depth and time.

Solaimanian and Kennedy (1993) proposed a simple method to estimate the maximum pavement temperature that considered the minimal amount of input, including maximum air temperature and hourly solar radiation. The technique is based on heat transfer theory and makes use of the effect of latitude on solar radiation. The fundamental equation of heat equilibrium in pavement is

$$q_{net} = q_s + q_a - q_c - q_k - q_r = 0 \tag{2-6}$$

where

q_{net}	=	the net rate of heat flow
q_s	=	absorbed energy from direct solar radiation;
q_a	=	absorbed energy from diffuse radiation (scattered from atmosphere);
q_c	=	energy transferred to or from the body due to convection;
q_k	=	energy transferred to or from the body due to conduction;
q_r	=	energy emitted from the body through outgoing radiation.

The energy absorbed by a pavement can be expressed as:

$$q_s = R_0 \alpha_1 \tau_a{}^{1/\cos z} \cos z \qquad (2\text{-}7)$$

where

R_0	=	solar constant equal to 442 Btu/(hr-ft^2),
z	=	zenith angle (latitude-solar declination angle),
α_1	=	surface absorbability (0.85-0.93),
τ_α	=	transmission coefficient for unit air mass, ranging from 0.81 on a clear day to 0.62 on a cloudy one.

The energy absorbed by pavement from atmospheric radiation can be estimated with the following equation

$$q_a = \varepsilon_a \sigma T_{air}^4, \qquad (2\text{-}8)$$

where

ε_α	=	the coefficient of atmospheric radiation
σ	=	Stefan-Boltzman constant equal to 0.1714×10^{-8} Btu/(hr-ft^2)
T_{air}	=	air temperature

The heat stream by the heat flow movement to the adjacent air is calculated by

$$q_c = h_c (T_s - T_{air}), \qquad (2\text{-}9)$$

where T_s is the pavement surface temperature, and h_c is the surface coefficient of heat flow.

The heat conduction rate under the pavement surface can be estimated as

$$q_k = -k \frac{T_x - T_s}{x}, \qquad (2\text{-}10)$$

where k is thermal conductivity, and T_x is the pavement temperature at depth x.

The outgoing radiation energy from the pavement surface can be given by:

$$q_r = \varepsilon \sigma T_s^4 , \tag{2-11}$$

ε is the emissivity of the pavement surface.

These models can be used to establish the following equation to calculate surface temperature by using air temperature, T_a:

$$422 \alpha_1 \tau_a^{1/\cos z} \cos z + \varepsilon_a \sigma T_a^4 - h_c (T_s - T_a) - \frac{k}{x}(T_s - T_x) - \varepsilon \sigma T_s^4 = 0 \ , \tag{2-12}$$

Maximum surface temperature can be estimated by this equation. The results show a good agreement between field measurements and the estimated values. The same energy balance equation was considered for calculating minimum surface temperature. Since the energy balance equation is valid at any time, and the energy balance equation for night time can be derived by considering zero solar energy during the night as follows,

$$q_{net} = q_a - q_c + q_k - q_r , \tag{2-13}$$

The equilibrium equation can be derived so:

$$\varepsilon_a \sigma T_a^4 - h_c (T_s - T_a) - \frac{k}{x}(T_s - T_X) - \varepsilon \sigma T_S^4 = 0 , \tag{2-14}$$

Usually during the night, surface temperature is lower than inside the pavement, which means q_k is positive, and the heat flows from the bottom of the pavement moving upward to the surface. The emissivity (ε) and thermal conductivity (k) of the pavement surface do not change, staying the same during daytime. However, the coefficient for atmospheric radiation (ε_α) and the surface coefficient of heat transfer (h_c) are not the same and have been changed. The surface coefficient of heat transfer depends on the surface, air temperature, and wind speed. Both surface and air temperatures are much lower at night. By using the empirical formula reported by Solaimanian and Kennedy, h_c was calculated to be between 1.4 and 2.5 Btu/(hr-ft^2-°F).

Similar to Dempsey and Thompson, Solaimanian and Kennedy's model also requires a significant amount of data on meteorological variables, weather condition, and thermal properties of pavement. The modeling process itself requires applying extensive heat transfer theories in addition to calculating several complex equations, which increases the potential accumulation of errors in the final results. Hermansson (2000) used equations derived by Solaimanian and Kennedy to establish a model to calculate the maximum summer temperature of pavement surface. The input data required for the models are air temperature, wind speed, and solar radiation. The results show good agreement between forecasted and observed temperatures.

Crevier and Delage (2001) developed a numerical model to forecast road surface conditions. The Model of the Environment and Temperature of Roads, known as METRo was developed to run at Canadian weather centers and was implemented first at the Ottawa Regional Centre in October of 1999. METRo uses data recorded by RWIS stations as input, together with meteorological forecasts from the operational Global Environmental Multiscale (GEM) model of the Canadian Meteorological Centre. METRo solves the energy balance at the road surface and the heat transmission in the road material to calculate the temperature evolution. METRo also considers water contaminants on the road surface in liquid and solid form. Solar fluxes hitting the pavement surface are taken from a GEM model as a function of cloud cover and temperature. METRo forecasts road conditions in three stages: initialization of the road temperature profile using previous records, coupling of the forecast with observed data during an overlap period, and then forecasting the pavement temperature itself.

METRo provides 24-h road condition forecasts two times per day, at 3:00 am and 3:00 pm local time. METRo is composed of three modules: the energy balance of the road surface, a heat-transmission module for the pavement material, and a module to take into account water, snow, and ice contaminant on the road surface. The model solves the energy balance equation regarding road surface and heat transmission in the pavement material to calculate temperature progression. The energy balance equation in METRo consists of seven terms of energy affecting road-condition forecasts: the incoming flux, the absorbed incoming infrared radiation flux, the emitted flux, the sensible turbulent heat flux, the latent heat flux, the flux associated with phase changes of precipitating water, and an anthropogenic flux (Crevier and Delage, 2001). In general, METRo is a very complicated model requiring a considerable amount of data input for estimation and calibration of equations. Maintaining and developing such large databases is extremely time consuming and costly. The research presents the results for a period from February 9 to May 1, 1999, for three stations in Ontario. METRo's overall frequency distribution of road temperature errors for 24 hour forecasting shows that about one-half of the forecasts lie within plus or minus 2K of the observed values. However, the research does not mention how accurate the forecasts are and does not evaluate the accuracy of forecasting short-term periods (less than 6 hours) compared to long-term periods.

2.6 Summary

This chapter reviewed the literature on previous research related to different modeling techniques for forecasting pavement surface temperature from meteorological variables and surface condition data. Road temperature forecasting is essential for effective road maintenance operations that increase road safety along maintenance routes and decrease negative environmental impacts of road-salt use. Recently, RWIS technology has gained increasingly wide popularity in North America as a means of gathering real-time information about road weather and surface conditions that can be used to improve winter maintenance operations. However, this technology requires a large number of stations to cover wide geographical areas and thus considerable amounts of resources for construction and maintenance of individual stations. Furthermore, RWIS stations are commonly designed for the purpose of monitoring current road conditions only, which limits their application for short-term planning of effective winter maintenance operations. RWIS data can be better used as input for models that can predict pavement surface temperature or other condition variables.

The literature review shows that most temperature-forecasting models aim at estimating maximum and minimum pavement temperature based on heat transfer theories. Those models are very complicated, involving a large number of variables and model parameters. Extensive efforts are required to calibrate and determine the values of these input variables. And due to limitation in data availability, many such values must be chosen arbitrarily, which could lead to compounded errors in final forecasts. In addition, these models are difficult to maintain. Some regression models have also been developed; however, their forecasting accuracy, reliability, and transferability remain problematic.

This research is intended to fill these gaps by applying simple statistical techniques to establish models to forecast pavement surface temperature using RWIS data. Two popular types of forecasting techniques, namely time series and artificial neural networks, are evaluated for their potential to predict pavement surface temperature from data provided by RWIS stations.

Chapter 3
Description of Study Site and Data

3.1 Introduction

In an effort to reduce winter road maintenance costs, road network authorities are using Road Weather Information Systems (RWIS) to obtain sufficient information for transportation network applications. The data recorded by RWIS stations allow agencies to manage winter maintenance operations more efficiently, reduce salt use, and provide a better level of service as a result. The Ministry of Transportation Ontario (MTO), with more than 165 RWIS stations across the province, plays a significant role in the deployment of winter maintenance operations (Buchanan, 2005). Figure 3.1 shows the RWIS network in Ontario's central region.

Figure 3.1: RWIS Network in Central Region of Ontario (Source: www.ogra.org)

The MTO is a member of the AURORA program, which is an international partnership of public agencies who work together to perform joint research activities in the area of road weather information systems (AURORA 2007). This chapter explains about our data source and where the data was extracted and maintained for the analysis purposes of this thesis.

3.2 Road Weather Information System (RWIS)

Technologies and equipment for winter maintenance operations have been developed over recent decades. In the past, visual inspection was more common to identify and predict snow amount on the road surface. Since the 1980s, Road Weather Information Systems (RWIS) have been used in Europe, and they are becoming more popular in North America (Crevier and Delage, 2001). An RWIS involves technology, including pavement and meteorological sensors located at Remote Processing Units (RPU), integrated with monitoring and predicting functions to employ real-time data, historical data, and computer models to forecast specific adverse pavement conditions for winter maintenance operations (Minsk, 1998). Real-time RWIS data is automatically collected every 20 minutes, 7-days per week and 24-hours per day, and uploaded within two minutes to a password-protected web portal where it is used to generate forecasts and archive them (AMEC 2007). Each station typically costs around \$70,000 (CAD) for installation and \$11,500 for annual operating cost (Buchanan 2005). Figure 3.1 shows an RWIS tower located at Hwy. 401/401 interchange in Toronto, Ontario.

Figure 3.2: A Typical RWIS Station

Multiple sensors embedded within the pavement are used to measure pavement and bridge surface temperature, often on multiple roads at an interchange (Bernstein et al., 2004). These sensors can also inspect and record conditions on the road surface and send them to RWIS towers. RWIS data can be used to predict when moisture is likely to freeze on the pavement surface, which helps winter maintenance authorities facilitate efficient deployment of maintenance crews. In addition, RWIS sensors can identify the presence of residual salt brine on the road surface. This information can be made available to maintenance authorities on a Local Area Network (Karlsson, 2001). Figure 3.3 is a typical RWIS pavement sensor, and Figure 3.4 shows some of the meteorological sensors installed on an RWIS tower.

Figure 3.3: RWIS Typical Pavement Sensor (Source: www.yorkregionsavealife.ca)

Figure 3.4: Meteorological Sensors Installed on RWIS Towers (Source: www.gis.esri.com)

3.2.1 Weather Variables Recorded by RWIS Stations

A typical RWIS station installed in Ontario records the following weather parameters: air temperature, dew point temperature, relative humidity, pressure, average wind speed, average wind direction, maximum gust wind speed, visibility, and precipitation state.

- Air temperature is the temperature of air measured at about 1.5 meters above ground in degrees Celsius.

- Dew point is the temperature to which air must be cooled to reach saturation at a constant atmospheric pressure in degrees Celsius. If the road temperature drops to dew point, moisture will appear on the road surface. The surface temperature and the amount of anti-icing/deicing chemicals (if any have been applied) are important in the development of ice or frost.

- Relative humidity (of an air-water mixture) is the ratio of the partial pressure of water vapor in the mixture to the saturated vapor pressure of water at a given temperature. A relative humidity of 0% means that the air contains no moisture, and a relative humidity of 100% shows that the air is saturated and cannot absorb any more humidity.

- Pressure is the force exerted by the weight of a column of air above a particular location (kPa).

- Wind speed is the average wind speed (km/h) during each recording interval (usually 20 minute intervals).

- Wind direction is the average wind direction during each recording interval. Wind direction is in degree format, and its value changes from 1 to 360.

- Maximum gust wind speed is the maximum wind speed (km/h) during recording intervals.

- Visibility is the greatest distance (in km) at which an object can be seen and identified in different weather conditions.

- Precipitation state is the state of precipitation, either raining or snowing lightly, moderately, or heavily.

3.2.2 Pavement Variables Recorded by RWIS Stations

Pavement sensors embedded on road surfaces record the following pavement variables: surface condition, surface temperature, freezing point, and subsurface temperature:

- Pavement surface condition (Sfc Cond) is a variable that reports the following road surface conditions: dry, wet, chemically wet, slushy, wet above freezing, wet below freezing, damp or frost touched, and whether a snow/ice watch, a snow/ice warning, or a black ice warning is advisable.

- Surface temperature (Sfc Temp) is the temperature of a road surface in degrees Celsius.

- Freezing point (Frz Point) is the temperature at which a liquid state changes to a solid in degrees Celsius. The temperature remains at this point until all the liquid has solidified. For example, the freezing point of water under standard atmospheric pressure is 0°C. For a given liquid under similar conditions, the freezing point and melting point are the same temperature.

- Subsurface Temperature (Sub Sfc Temp 40 cm) is the pavement temperature in degrees Celsius approximately 40 cm below the surface. Additional sensors may also be installed to record pavement temperature at 1.5 m below the surface.

3.3 RWIS Location

The data used in this paper were obtained from a RWIS station located on Hwy. 401 near Toronto, Ontario. The station is called CR-17 (CR stands for central region). Figure 3.5 shows the location of CR-17. The data set consists of records from pavement and weather sensors at an interval of 20 minutes. Pavement sensors are embedded in pavement, providing data that includes surface temperature, surface condition, and freezing point, while weather sensors were installed on a tower 10 meters from the ground, providing data on air temperature, dew point, relative humidity, pressure, wind speed and direction, maximum gust wind speed, and precipitation state.

Figure 3.5: The Location of CR-17 in the RWIS Network

3.4 Data Period

An investigation was conducted to find out the optimal number of days of data that should be used for model calibration. Five specific benchmark dates were selected during winter 2007 to cover the season (February 4th, 10th, 15th, and March 4th, 10th). For each benchmark, a one-day, one-week, two-week, and three-week length of dataset was considered for the proposed model. The Root Mean Square Error (RMSE) was calculated for each model to figure out which data length creates minimum errors. The statistical analysis shows that using two weeks of data is the best in terms of model calibration and generalization. Figure 3.6 shows RMSEs for all benchmark dates.

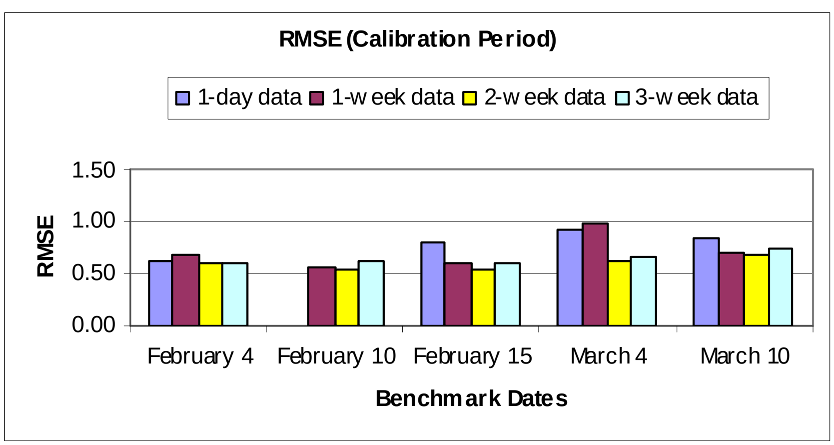

Figure 3.6: Comparison of Root Mean Square Error for All Benchmark Dates

The final data set used for comparing alternative models includes a total of 14 consecutive days from Jan. 22 to Feb. 4 of 2007. Observations were aggregated into hourly averages for the convenience of developing hourly forecasting models. A weighted interpolation approach was applied to fill out the missing observations. The final data set was divided into two subsets with the first 13 days of data for model calibration and the remaining day as a holdout for model validation.

Chapter 4
Data Analysis Procedure

This chapter discusses the results of a comparative analysis on forecasting road surface temperature using time series and artificial neural networks from the data recorded by the RWIS station described previously. A time series method is used first to establish forecasting models by applying historical surface temperature as the dependent and air temperature as the independent variable. Then artificial neural networks are applied to the dataset to establish other feasible models.

4.1 Time Series Analysis

The primary objective of this analysis is to develop time series models by considering the temporal variation pattern of temperature as well as the impacts of weather factors on road surface temperatures. The time-series approach was selected because of the time-dependent nature of the pavement temperature and weather variables involved. A time series is a statistical method that can be used to establish periodic functions to forecast the objective values of such properties as a function of time. In the literature, researchers have applied this technique in characterizing the seasonal variations of pavement structural properties (Ali & Parker 1996); however, using a time series in forecasting pavement temperature is a relatively new undertaking.

The most commonly used time series model is Seasonal Autoregressive Integrated Moving-Average (SARIMA), which provides powerful and flexible options for modeling trend and seasonal components in a variable such as road surface temperature (Box et. al., 1976). Furthermore, predictor variables may be added to a SARIMA model as is done with traditional regression models.

With the equally sequenced values of a stationary stochastic process z denoted by z_t, z_{t-1},…, an Auto Regressive Moving Average model ARMA (p,q) for this process can be expressed as (Box et al., 1976):

$$Z_t = c + \sum_{i=1}^{p} \phi_i z_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \qquad (4\text{-}1)$$

where c, ϕ_i and θ_j are the model parameters to be estimated, and ε_t is assumed to be an independently and identically distributed (i.i.d.) normal random variable with mean zero and variance σ_ε^2. Using the backward shift operator B, i.e., $Bz_t = z_{t-1}$, equation 4-1 can be written as:

$$\phi(B)z_t = \theta(B)\varepsilon_t \tag{4-2}$$

where $\phi(B) = 1- \phi_1 B - \ldots - \phi_p B^p$ is the auto regressive operator AR(p), $\theta(B) = 1- \theta_1 B - \ldots - \theta_q B^q$ is the moving average operator MA(q). Conceptually, an autoregressive process is one with a "memory," in that each value is correlated with all preceding values. In an AR (1) process, the current value is a function of the preceding value, which is a function of the one preceding it, and so on. Thus, each shock or disturbance to the system has a diminishing effect on all subsequent time periods. For example, in a consideration of daily data, a non-seasonal AR(1) process would model temperature value at 8 a.m. on Tuesday based on temperature at 7 a.m. at the same day.

The moving-average (MA) component of an ARMA model tries to predict future values of the series based on deviations from the series mean observed for previous values. In a moving-average process, each value is determined by the weighted average of the current disturbance and one or more previous disturbances. The order of the moving-average process specifies how many previous disturbances are averaged into the new value. In the standard notation, an MA (n) process uses n previous disturbances along with the current one.

The ARIMA model assumes a stationary process that requires stability in the mean and variance of the process; however, most real-life processes do not meet these requirements. A non-stationary state in the variance is dealt with Box-Cox power transformations, which are defined as $u_t = (z_t^\lambda - 1)/ \lambda$ for $\lambda \neq 0$. For a given model, the optimal value of λ is found by minimizing the sum of squares of the residuals of the model. In case λ turns out to be equal or close to zero, a natural logarithmic transformation $u_t = \ln(z_t)$ is considered (Box et al., 1976). On the other hand, a non-stationary state in the mean is commonly addressed by first differencing the original process and then modeling the resulting process. For example, a process of one difference order is $z_t - z_{t-1}$. The d^{th} order differenced process is denoted by $v_t = (1- B)^d z_t$. The ARMA (p,q) model for the differenced process v is referred to as the Auto Regressive Integrated Moving Average model ARIMA (p,d,q) for the process z. The differencing or integration component of an ARIMA model tries, through differencing, to make a series stationary. Time series often reflect the cumulative effect of some process that is responsible for changes in the level of the series but is not responsible for the level itself. A series that measures the cumulative effect of something is called integrated.

An ARIMA model can also be conveniently extended to model seasonality in a process. The resulting model is referred to as Seasonal ARIMA or a SARIMA model, with the following form:

$$\phi_p(B)\Phi_P(B^S)(1-B)^d(1-B^S)^D z_t = \theta_q(B)\Theta_Q(B^S)\varepsilon_t \tag{4-3}$$

where $\phi_p(B)$ and $\theta_q(B)$ are non-seasonal AR(p) and MA(q) operators; $\Phi_p(B^S)$ and $\Theta_q(B^S)$ are seasonal AR(P) and MA(Q) operators; and B^S is the seasonal backward shift operator, which is defined as $B^S z_t = z_{t-s}$. For hourly data, s = 24 indicates daily seasonality. For the same example on daily temperature data, a seasonal AR(1) process would model the temperature value at 8 a.m. on Tuesday based on the temperature value at 8 a.m. on the day before (Monday). These components are used to explain significant correlations found in the autocorrelation factor (ACF) and partial autocorrelation factor (PACF), as elaborated on later sections.

Box-Jenkins (1976) proposed a three-stage procedure, including identification, estimation, and diagnostic checking, that is now commonly used in developing time-series models. The Box-Jenkins procedure is also adopted in this research. In the identification stage, the time series data is evaluated using the estimated autocorrelation function (ACF) and partial autocorrelation function (PACF), to select a tentative model. In the estimation stage, using a maximum likelihood approach, the parameters of the model are estimated. In the last stage, diagnostic checking, the residuals of the model are inspected for the i.i.d. assumption and, in case of failure, the tentative model is improved until it is acceptable. Normalized residuals time domain plots, residuals ACF, the Ljung- Box statistics (Box et al., 1994), residuals probability plots, and plotting residuals against the fitted values are popular tests in the diagnostic checking stage.

4.1.1 Uni-variable Time Series Model

The model developing process is carried out using the Statistical Package for Social Science (SPSS®, Version 15). The first step is to plot the series and look for any evidence that the mean or variance is not stationary, because the SARIMA procedure assumes that the original series is stationary; otherwise, it must be converted to a stationary series. Figure 4.1 shows a sequence plot of surface temperature from January 22 to February 4 as a sample period to validate and calibrate the model. The figure shows an upward trend, which makes it clear that the series is not stationary and requires conversion to a stationary series.

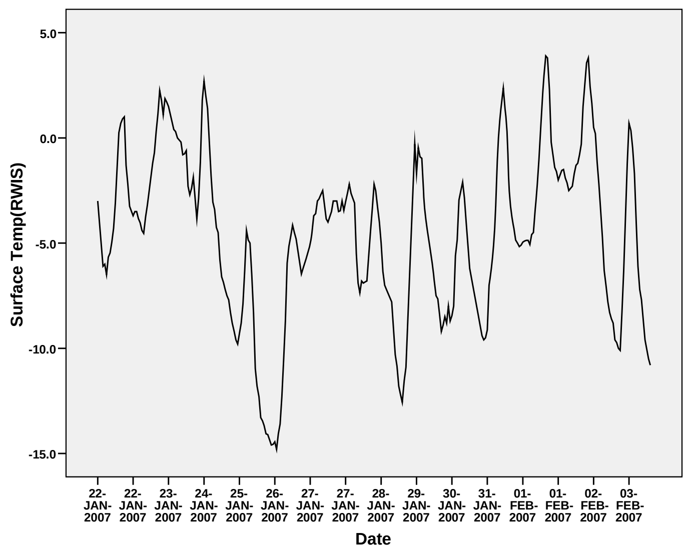

Figure 4.1: Sequence plot of surface temperature from January 22 to February 4

The configuration and number of peaks suggests the presence of seasonal components during each 24 hours per day as a cycle.

Autocorrelation plots (Box et. al., 1976) are common tools for checking randomness in a data set. This randomness is ascertained by computing autocorrelations for data values at varying time lags. If random, such autocorrelations should be near zero for each time-lag separation. If non-random, then one or more of the autocorrelations will be significantly non-zero. In addition, autocorrelation plots are used in the model identification stage for Box-Jenkins autoregressive, moving average time series models. Inspection of the slow decrease in the autocorrelation plot (Figure 4.2) separated by seasonal interval (24 lags) confirms that seasonal differencing is required because, after each 24 lag, the absolute amount of coefficient rises to its maximum and then decreases, showing a periodic pattern.

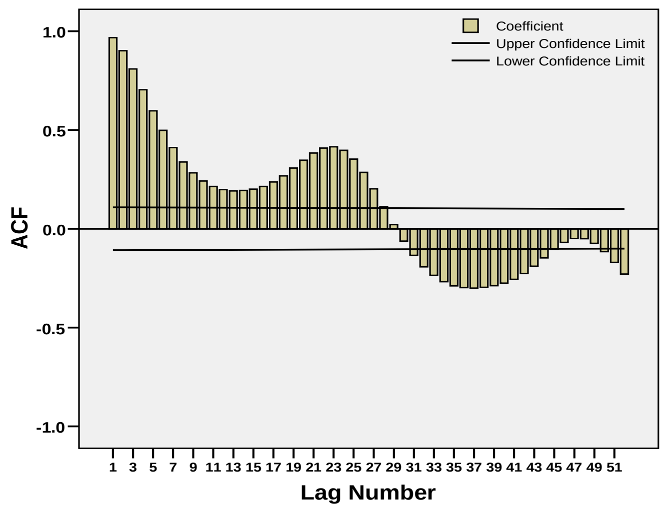

Figure 4.2: Autocorrelation plot for surface temperature

The seasonal chart presented in Figure 4.3 shows the results of one-time seasonal differencing which means applying natural logarithmic transformation to the data. Although those seasonal spikes in Figure 4.1 have been reduced significantly, an upward trend can still be observed in Figure 4.3, which suggests a non-seasonal differencing.

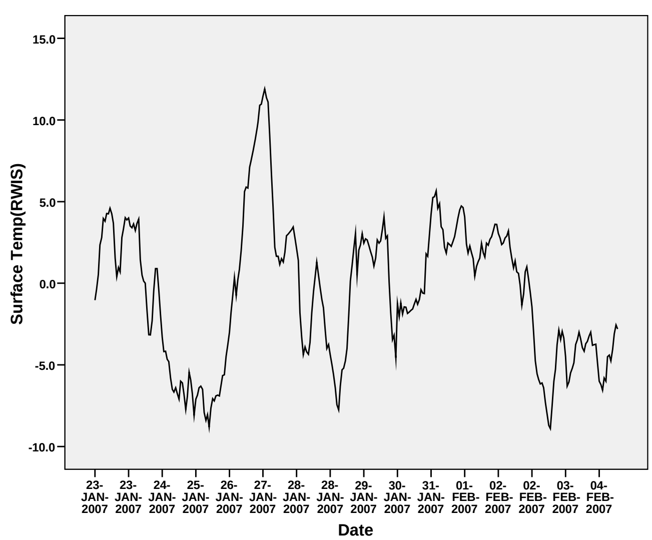

Figure 4.3: Plot of surface temperature after one seasonal differencing

Figure 4.4 shows the sequence chart after one seasonal and one non-seasonal differencing have been applied, meaning that natural logarithmic transformation has been applied one time to a 24-hour data period as well as a 1-hour data period. The mean of the differenced series appears to be 0, and the upward trend in the original series has been removed.

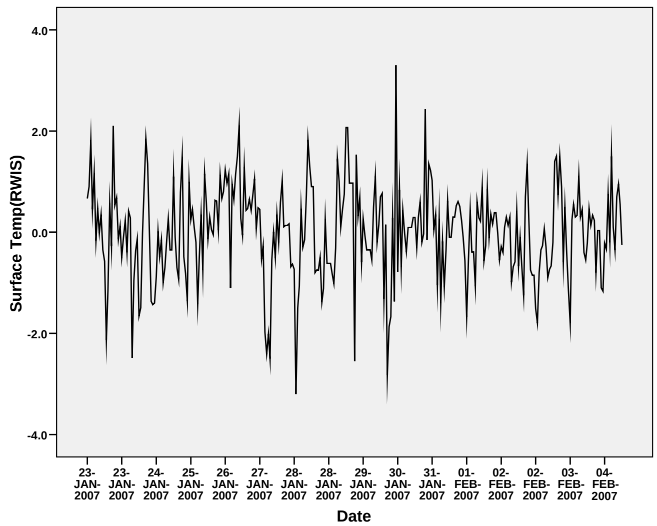

Figure 4.4: Plot of surface temperature after one non-seasonal and one seasonal differencing

The Autocorrelation Factor (ACF) plot of two-time differenced series (Figure 4.5) will show if additional differencing is required. The figure shows that two-time differencing has removed the slow decay of the ACF over lags, and there is no evidence that further differencing, either seasonal or non-seasonal, is required. The conclusion is that one order each of seasonal and non-seasonal differencing is sufficient for stabilizing the series.

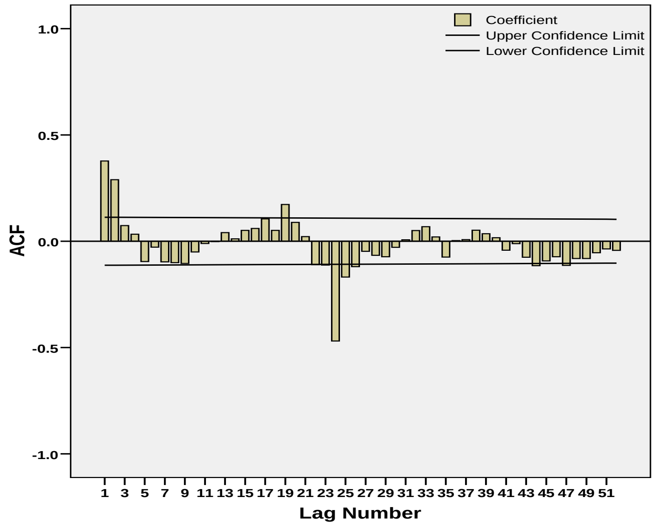

Figure 4.5: Autocorrelation plot after one order of seasonal and non-seasonal differencing

The next step in modeling the series involves examination of autoregressive and moving-average orders. These orders can be estimated by ACF (Figure 4.5) and PACF of the two-time differenced series (Figure 4.6).

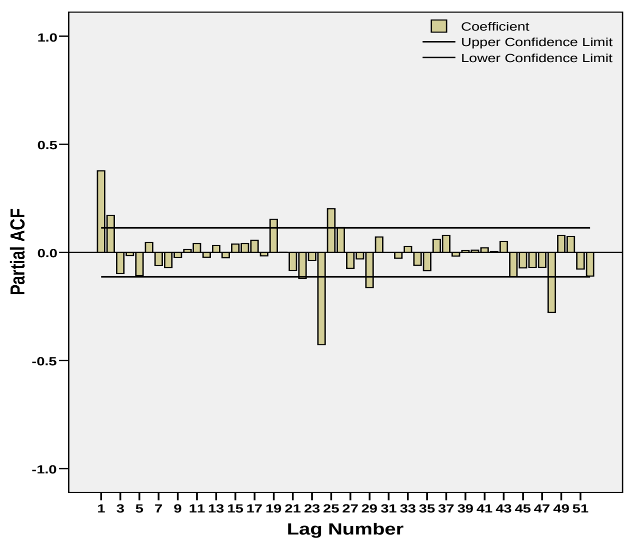

Figure 4.6: Partial ACF plot after one order of seasonal and non-seasonal differencing

After evaluating a number of alternative time series models based on the exploratory analysis discussed previously, the best fit uni-variable model is a SARIMA (0,1,2)(0,1,1). Table 4.1 summarizes the calibration results, which indicate that the model explained a good amount of variation (54.6%) with a small RMSE (0.637). The Ljung-Box statistic (Ljung and Box, 1978) is significant (<0.05), implying that there is structure in the data that is not accounted for the model. Based on this finding, an alternative model with predictors was attempted as described in the following section.

Table 4.1: SARIMA Model without Predictor (Uni-variable Model)

a) Model parameters

Model			Estimate	SE	t	Sig.
SurfTemp	Difference		1			
	MA	Lag 1	-.370	.057	-6.457	.000
		Lag 2	-.268	.057	-4.681	.000
	Seasonal Difference		1			
	MA, Seasonal	Lag 1	.850	.067	12.675	.000

b) Model statistics

Model	Number of Predictors	Model Fit statistics		Ljung-Box			Number of Outliers
		Stationary R-squared	RMSE	Statistics	DF	Sig.	
SurfTemp	0	.546	.637	13.466	16	.566	0

The equation for the Uni-variable model is

$$(1-B)(1-B^{24})Ln(SurfTemp_t) = (1+0.37B+0.27B^2)(1-0.85B^{24}) \qquad (4\text{-}4)$$

where $SurfTemp_t$ is surface temperature and B is backward shift operator.

4.1.2 Multi-variable Time Series Model

The uni-variable model discussed previously includes only the dependent variable itself, that is, the surface temperature. It does not include information from any other variables that may have an important effect on or association with the surface temperature. The objective of this section is to establish a better forecasting model by considering surface temperature as a dependent variable and weather factors as independent variables. SARIMA treats these variables much like predictor variables in regression analysis by estimating the coefficients that best fit the data. The included variables need to be predicted externally, which has been assumed available from other sources. Using SPSS®, the weather variables were added to the SARIMA model. Weather variables considered in the analyses were air temperature, dew point temperature, relative humidity, pressure, average wind speed and direction, maximum gust wind speed, precipitation, and freezing point. Table 4.2 provides estimates of the model parameters and associated significant values, including SARIMA coefficients as well as weather predictors.

Table 4.2: SARIMA (Multi-var) model and weather predictor coefficients

Variables		Estimates	Std Error	t	Approx Sig
Non-Seasonal Lags	MA1	1.243	.314	3.960	.000
Seasonal Lags	Seasonal MA1	.875	.090	9.754	.000
Regression Coefficients	Air Temp.	.918	.054	17.085	.000
	Dew Point Temp.	-.154	.053	-2.875	.004
	Relative Humidity	.003	.018	.185	.854
	Pressure	-.277	.179	-1.547	.123
	Average Wind Speed	-.012	.009	-1.326	.186
	Average Wind Direct.	.000	.000	-.467	.641
	Max Gust Wind Speed	.017	.010	1.816	.070
	Precipitation	.188	.114	1.651	.100

The last column in Table 4.2 implies that only air temperature and dewpoint are significant predictors in the model. Since the significance level of a variable might change if non-significant variables are removed, another try was conducted including air temperature, dewpoint, and maximum gust wind speed as the three variables of higher significance. However, air temperature and dewpoint stayed as the most significant independent variables in the model. When two or more random variables (air temperature and dewpoint) are defined on a probability space, it is important to evaluate how they vary together. The term multicollinearity is used to indicate the incidence of linear relationships among the independent variables. If two or more of the independent variables are highly correlated, the precision of a model falls, and it becomes very difficult to separate the relative influences of different independent variables. Table 4.3 shows the correlation matrix for RWIS data.

Table 4.3: Correlation Matrix of RWIS Variables

Variables	Surf Temp	Air Temp	Dew Point Temp	Relative Humidity	Pressure	Avg Wind Speed	Avg Wind Dir	Max Gust Wind Speed	Precip	FrzPt
Surf Temp	1.00									
Air Temp	0.87	1.00								
Dew Point Temp	0.79	0.96	1.00							
Relative Humidity	0.08	0.31	0.55	1.00						
Pressure	-0.60	-0.71	-0.73	-0.40	1.00					
Avg Wind Speed	-0.01	-0.11	-0.25	-0.52	0.07	1.00				
Avg Wind Dir	-0.07	-0.11	-0.23	-0.43	0.25	0.30	1.00			
Max Gust Wind Speed	0.01	-0.09	-0.24	-0.53	0.05	0.96	0.27	1.00		
Precip	0.02	-0.01	0.06	0.21	-0.10	-0.13	-0.27	-0.13	1.00	
FrzPt	-0.38	-0.45	-0.52	-0.44	0.39	0.18	0.21	0.17	-0.05	1.00

Table 4.3 shows that surface temperature has a high correlation with air temperature (87%) and dewpoint temperature (79%). Furthermore, there is a very high collinearity between air temperature and dewpoint temperature (96%), which confirms that there is a linear relationship between these two independent variables. To avoid multicollinearity in the model, we decided to include only air temperature as an independent variable in further analysis.

A number of alternative multi-variable models were tested, and the best model was SARIMA (0,1,1)(0,1,1), with air temperature being the only significant independent variable. Table 4.4 summarizes the calibration results. Note that the estimated coefficient for air temperature is 0.862, which suggests a positive association with the road surface temperature as expected. Compared to the uni-variable model, this model has a much higher stationary R-squared (0.757 vs. 0.546), and lower RMSE (0.482°C vs. 0.637°C). Stationary R-squared is the coefficient of determination of an ARIMA (0,1,0)(0,1,0) model as used by Harvey (Harvey, 1989). The Ljung-Box statistic is not significant at 0.05, suggesting that the model is correctly specified.

Table 4.4: SARIMA Model with Predictor

a) Model parameters							
Model				Estimate	SE	t	Sig.
SurfT	SurfTemp	Difference		1			
		MA	Lag 1	-.249	.058	-4.317	.000
		Seasonal Difference		1			
		MA, Seasonal	Lag 1	.860	.076	11.312	.000
	AirTemp	Numerator	Lag 0	.862	.045	19.212	.000
		Difference		1			
		Seasonal Difference		1			

b) Model statistics							
Model	Number of Predictors	Model Fit statistics		Ljung-Box			Number of Outliers
		Stationary R-squared	RMSE	Statistics	DF	Sig.	
SurfT	1	.757	.482	18.362	16	.303	0

The equation for the Uni-variable model is

$$(1-B)(1-B^{24})Ln(SurfTemp_t) = (1+0.25B)(1-0.86B^{24}) + 0.86(1-B)AirTemp_t \qquad (5\text{-}4)$$

where $SurfTemp_t$ is timely observation of surface temperature and B is backward shift operator.

4.2 Artificial Neural Networks

Artificial Neural Networks (ANN) are among the most popular modeling and problem-solving techniques used in the fields of artificial intelligence, science, and engineering. In general, an artificial neural network is a non-linear statistical model for mapping inputs to output. With their unique model structure, ANN models have been found effective for addressing a wide range of problems, such as image processing and recognition, function approximation and regression, and data processing (Rumelhart, 1987; Bishop, 1995). In this research, ANN is applied to forecast road surface temperature as an alternative to the time series approach described previously.

ANN data processing is based on the idea of simple processing units that work in parallel together. These processing units, also called artificial neurons or simply neurons, are linked into networks via direct connections. The main characteristic of such a computing structure is that a number of highly interconnected neurons work together to solve specific problems with a step-by-step approach. ANN's are capable of learning through a learning process that involves adjustments to the connections that exist between the neurons. ANN learns to emulate required input-output mapping by adapting its connections.

4.2.1 Artificial Neural Network Architecture

Many different neural network structures have been proposed, some based on biologists observations, and some based on mathematical approaches. The most common structure or network used by researchers is called a back-propagation neural network. As shown in Figure 4.7, a back-propagation neural network is formed in three layers, called the input layer, hidden layer, and output layer. Each layer comprises one or more nodes, represented in this diagram by small circles. The links between the nodes indicate the flow of information between nodes, and from the input towards the output. Other types of neural networks might have more intricate links, such as feedback paths.

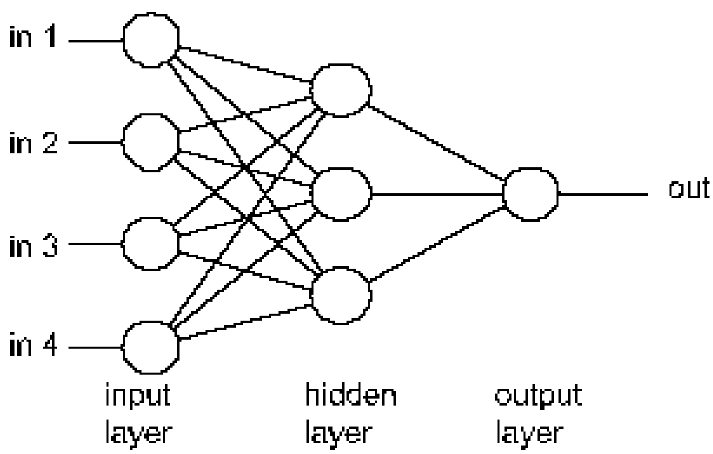

Figure 4.7: Artificial Neural Network Architecture (source: www.imtech.res.in)

The nodes of the input layer are passive, which means they do not change or modify the data. In contrast, the nodes of the hidden and output layer are active, which means they modify the data. The duplicated values of the input layer are sent to all the nodes in the hidden layer. As shown in Figure 4.8, the values entering a hidden node are multiplied by a set of predetermined numbers, known as weights. The weighted inputs are then added to generate a single number. This number is passed through a nonlinear mathematical function known as a sigmoid, which has an “s” shaped curve that limits the node’s output.

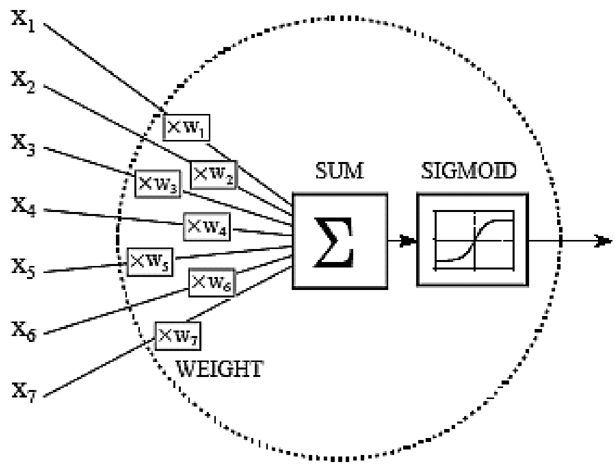

Figure 4.8: Neural Network Active Node (source: www.dspguide.com/ch26/2.htm)

A sigmoid function is used to set the output value of any given neuron by processing the sum of the weighted input values and any bias applied. The sigmoid function outputs a value that is close to zero for a low total input value and close to one for a high input value. The slope of the function curve can be adjusted by including a threshold value that can make the “step” between zero and one steeper or more shallow. The formula for a sigmoid function is $1/(1+e^{-sx})$, where x is the sum of the weighted connection values and any bias, and s is any threshold (scale) value being applied by the neuron (http://www.adit.co.uk/html/programming_a_neural_network.html). Neurons can use any differentiable transfer function to generate their output. Multilayer networks often use the log-sigmoid transfer function known as logsig (Figure 4.9).

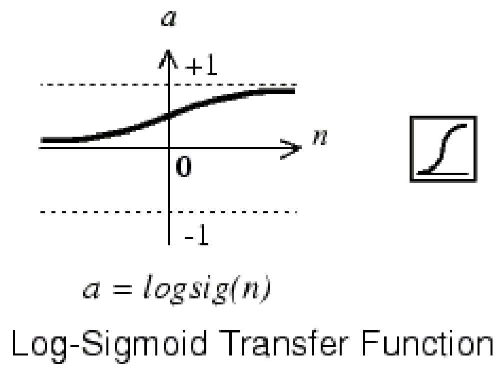

Figure 4.9: A Typical Log- Sigmoid Transfer Function (source:www.mathworks.com)

The function logsig generates outputs between 0 and 1 as the neuron's net input goes from negative to positive infinity. Alternatively, multilayer networks can use the tan-sigmoid transfer function known as tansig (Figure 4.10).

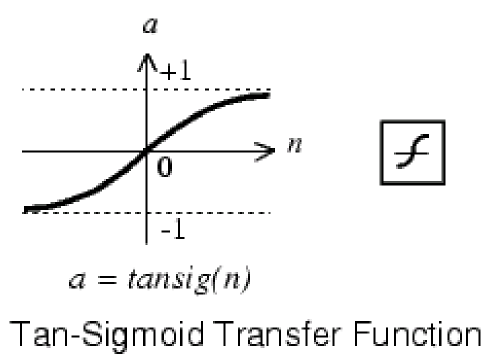

Figure 4.10: A Typical Tag- Sigmoid Transfer Function (source: www.mathworks.com)

Occasionally, the linear transfer function known as purelin is used in backpropagation networks (Figure 4.11).

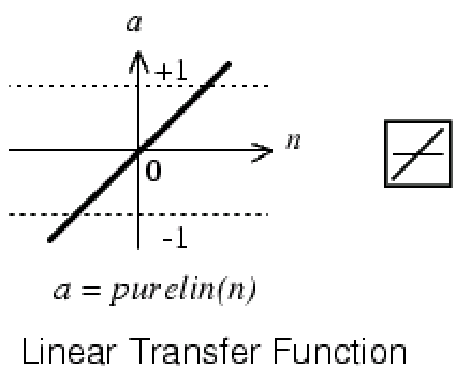

Figure 4.11: A Typical Linear Transfer Function (source: www.mathworks.com)

Neural networks can consist of unlimited layers and unlimited nodes per each layer. Most applications, however, use the three-layer structure, with a maximum of a few hundred input nodes. The hidden layer is usually about 10% the size of the input layer (Smith, 1998, www.dspguide.com/ch26/2.htm). In most cases, the output layer needs only a single node, as is being considered in this research.

4.2.2 Training and Validation of Artificial Neural Networks

Development of ANN models generally involves three steps:

- Model selection: Selection depends on the data representation and the application. Excessively complex models tend to lead to problems with learning procedures.

- Learning algorithm: There are numerous tradeoffs among learning algorithms. Any algorithm is likely to work well with the appropriate parameters for training on a particular fixed dataset. However, selecting and tuning an algorithm for training requires considerable experimentation.

- Robustness: If the model, learning algorithm, and cost function are selected properly, the resulting network can be extremely robust.

ANNs have the ability to learn, and given a sufficient set of training data, are capable of generalizing results based on new data. However, this ability is restricted within the parameter space initially established by the training set. Of significance to the success of ANN training is the selection of transfer function, learning parameters, and training data. To complete the basic design of the ANN architect, the number of neurons in the hidden layer has to be determined by experiment. For our network, we decided that some experimentation with the number of neurons would be acceptable, assuming a minimum overall error for a given number of epochs. Optimization and validation of ANN performance is accomplished by analysis on training rates and number of hidden layer neurons. Once good training parameters are identified, they are used to train the ANN until convergence is achieved. Once trained using the determined parameters, the ANN needs to be verified. We assessed the final ANN using both training data and test data.

As discussed previously, the ANNs used in this analysis are back-propagation networks consisting of three layers: the output, hidden, and input layers. The output layer includes cells representing the variables to be estimated -- in this case the road surface temperature at time t ($SurfT_t$). The input layer represents factors that may have an impact on the pavement temperature. The input variables were set to be similar to those used in the multi-variable time series model discussed previously, including $AirT_t$, $SurfT_{t-1}$, $SurfT_{t-2}$ and $SurfT_{t-24}$. The number of hidden layers and the number of hidden nodes in each layer are determined through a trial-and-error process by training and testing the performance of a set of alternative ANNs. While computationally different, training an ANN is in essence the same as calibrating a regression or time-series model (Fine, 1991). We used MATLAB to calibrate the ANN models. The following table (Table 4.4) shows the alternatives that were considered to the find best architecture for the transfer function.

Table 4.5: Alternative transfer functions in layer 1(hidden) and layer 2(output)

Transfer Function in Layer 1	Tansig	Tansig	Tansig	Purelin	Purelin	Purelin	Logsig	Logsig	Logsig
Transfer Function in Layer 2	Tansig	Purelin	Logsig	Tansig	Purelin	Logsig	Tansig	Purelin	Logsig
MSE	28.01	0.33	36.71	28.05	0.46	36.72	28.15	0.38	36.99

The table shows that a network with a Tansig transfer function for the hidden layer and Purelin transfer function for the output layer results in a minimum Mean Square Error (MSE) equal to 0.33.

In the next step, we tried to find the number of neurons in the hidden layer according to our selected network. This is possible by checking different numbers of neurons in the hidden layer and finding the one with the minimum MSE. Table 4.5 shows the MSE associated with the number of neurons in the hidden layer of the selected network.

Table 4.6: The mean square error associated with the number of neurons

No. of Neurons	5	8	10	12	15
MSE	0.39	0.33	0.30	0.34	0.35

This table implies that 10 neurons in the hidden layer cause the minimum amount of MSE equal to 0.30

The same 14 days of hourly temperatures were used to train (or calibrate) and test a number of ANNs with different combinations of hidden layers and hidden nodes. It was found that an ANN with 3 layers, in which the hidden layer includes 10 nodes with a hyperbolic tangent sigmoid transfer function, performed best and is thus used in our subsequent analysis. The ANN was trained for a total of 1000 training epochs, and at the end of the training epoch, the training (calibration) RMSE is 0.505°C. Figure 4.9 shows the training results, which gives a RMSE of 0.770°C.

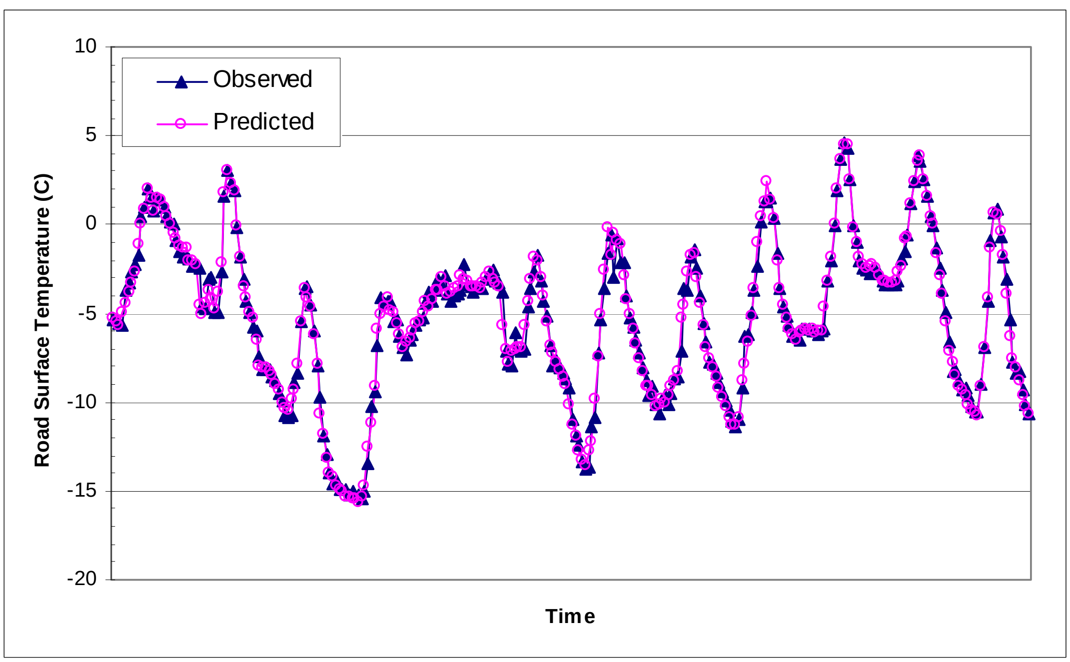

Figure 4.12: ANN Training Results: Observed vs. Predicted

4.3 Model Comparison

To compare the proposed models, the calibrated models were applied to make 1-hr and 3-hr ahead forecasting for the holdout day. For 3-hrs ahead forecasting, each of the proposed models was applied recursively to forecast the next hour's temperature. Figures 4.14 and 4.15 show the predicted pavement temperatures by the individual models as compared to the surface temperature provided by the RWIS.

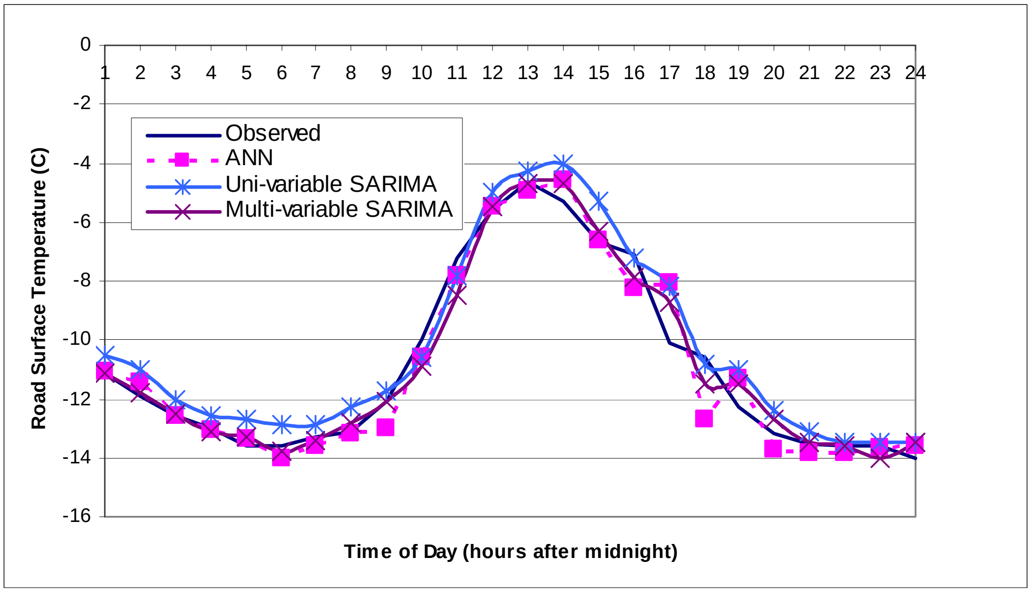

Figure 4.13: Comparison of Forecasted and Observed Temperature, 1-hr ahead

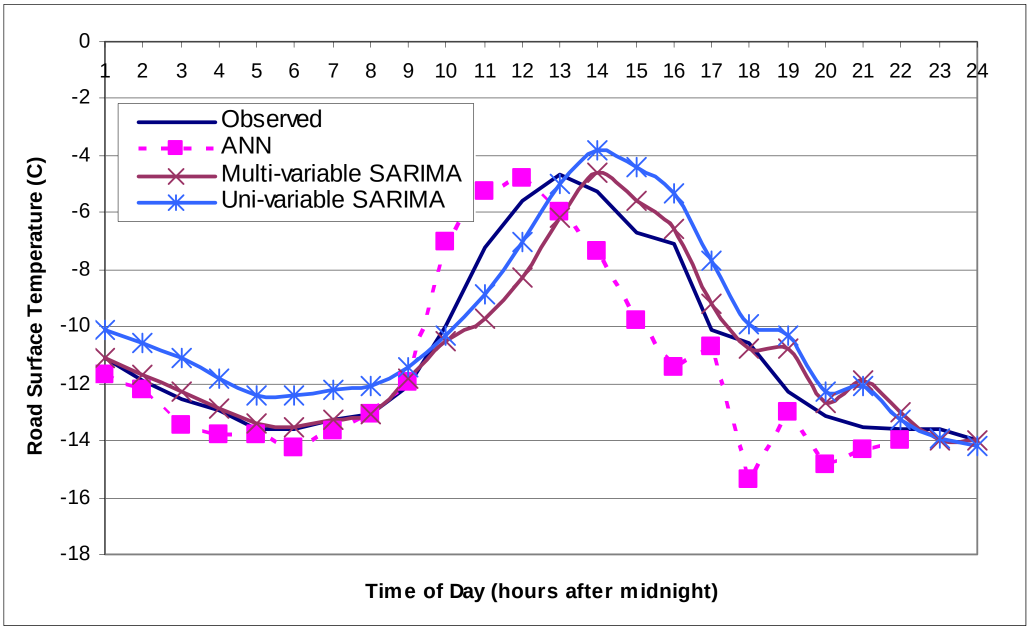

Figure 4.14: Comparison of Forecasted and Observed Temperature, 3-hr ahead

Table 4.7 compares the RMSE of all three models for both calibration and validation data, and Figures 4.16, 4.17, and 4.18 show RMSE for the calibration period and validation period of 1-hr and 3-hr ahead of time. It can be seen that multi-variable SARIMA has the lowest RMSE in both 1-hr and 3-hr ahead forecasting. The uni-variable model has a fairly low RMSE for the 3-hr ahead forecast; however, its performance deteriorated when used for 1-hr ahead forecasting. Note that the uni-variable model is also the only model that does not require forecasting on the predictor, that is, air temperatures. The ANN model is comparable with the multi-variable SARIMA model.

Table 4.7: Comparison of Calibration and Validation Results of Alternative Models

Model	RMSE (Calibration)	RMSE (Validation 1hr ahead)	RMSE (Validation 3hr ahead)
Uni-variable SARIMA	0.66	0.80	1.31
Multi-variable SARIMA	0.48	0.58	1.02
ANN	0.51	0.77	1.52

In our validation analysis, we had assumed that the air temperature could be estimated without any estimation error. As a result, the relative performance of other models depends on the quality of forecasting on air temperature.

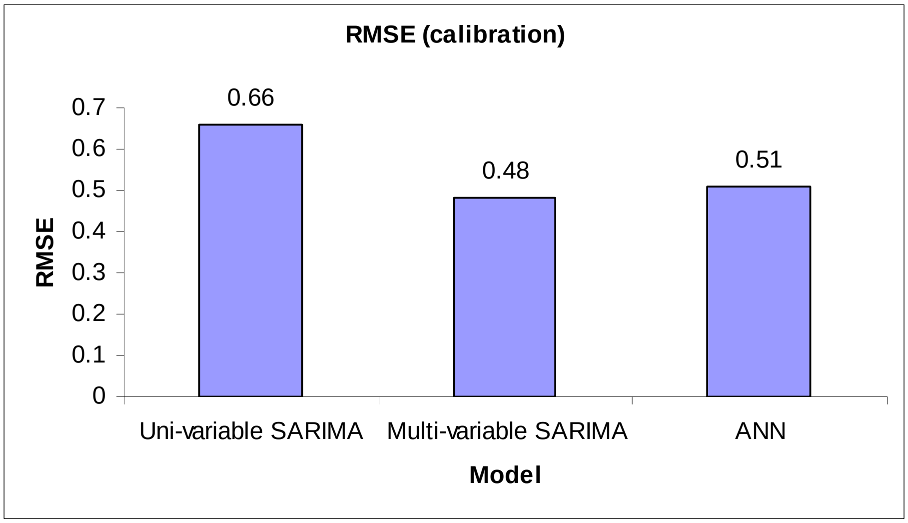

Figure 4.15: RMSE of Models during Calibration Period

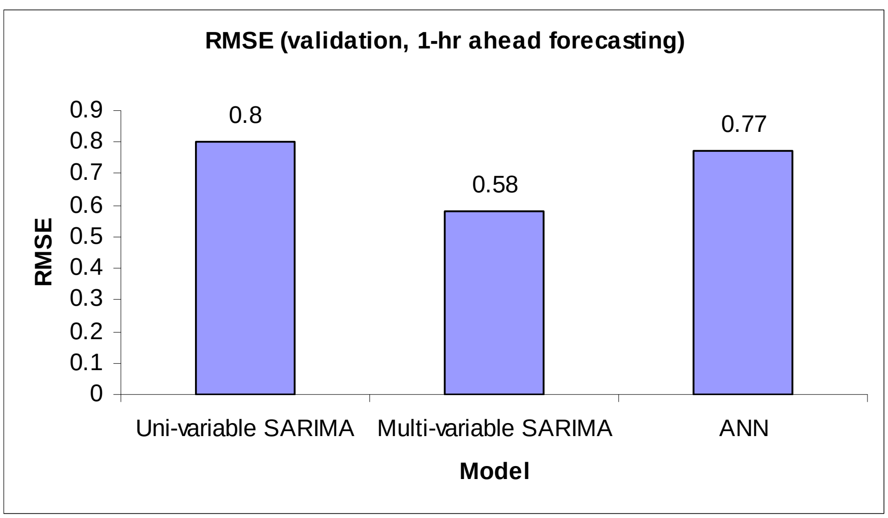

Figure 4.16: RMSE of Models during Validation Period (1-hr ahead)

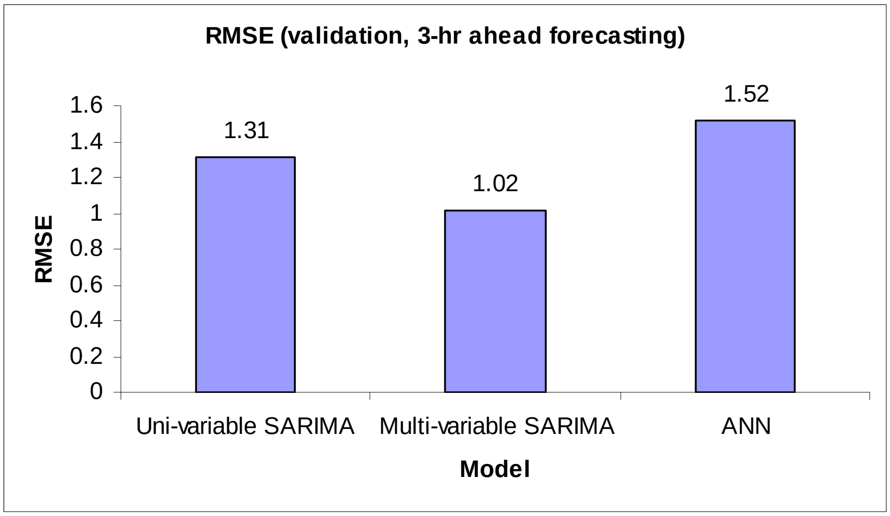

Figure 4.17: RMSE of Models during Validation Period (3-hr ahead)

It should also be noted that in our previous multiple-step ahead analysis (e.g., 3-hr ahead) forecasting was done through recursive applications of 1-hr ahead forecasting models. While this is a common practice in time-series analysis, an alternative is to develop separate models for different forecasting horizons. For example, a separate model could be developed for 3 hrs or 5 hrs forecasting horizons. This approach has the advantage of avoiding possible error propagation in a recursive process. To illustrate this problem, we calibrated two additional ANN models with 3 hrs and 5 hrs forecasting horizons respectively. Figures 4-16 and 4-17 show the 3 hrs and 5 hrs forecasting results using respective separate models as compared to those using a 1-hr ahead forecasting model. The results show significant improvement of the dedicated models as compared to recursive application of the 1-hr ahead model. This result also suggests that specially trained many steps ahead ANN models may have the advantage over multivariable SARIMA models.

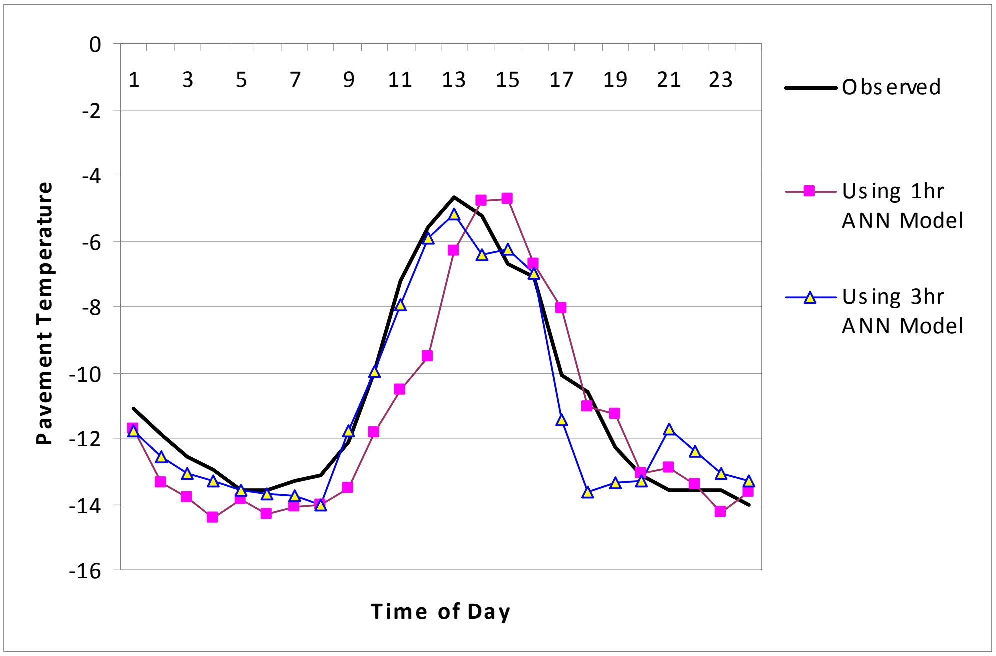

Figure 4.18: 3 hrs Ahead Forecasting

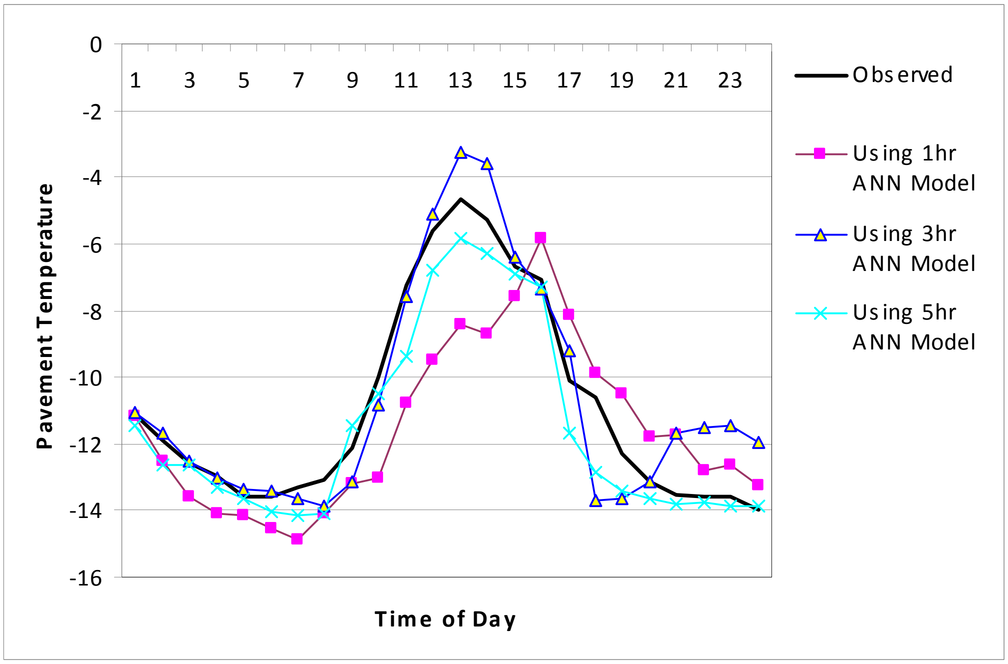

Figure 4.19: 5 hrs Ahead Forecasting

Chapter 5
Conclusions and Recommendations

Forecasting road surface temperature is a challenging and elusive undertaking due to large variations in data requirements such as weather, traffic, and road conditions. This research has attempted to establish simple statistical models to forecast pavement temperature using data recorded by RWIS stations.

An extensive review of literature was carried out relevant to pavement forecasting models in chapter 2. Data recorded by an RWIS station located on Hwy 401 in Toronto was used for the analysis. The data set consists of recordings from pavement and weather sensors at an interval of 20 minutes. Observations were aggregated into hourly averages for the convenience of developing hourly forecasting models. A weighted interpolation approach was applied to fill in the missing observations. As a result, the final data set used for comparing alternative models includes a total of 14 consecutive days from Jan. 22 to Feb. 4 of 2007. The final data set was divided into two subsets with the first 13 days of data used for model calibration and the remaining day as a holdout for model validation.

This chapter covers a summary of the major findings from the research followed by several recommendations.

5.1 Summary of Conclusions and Major Findings

This research conducted a comparative analysis of the performance of several alternative modeling techniques for short-term forecasting of road surface temperatures at a specific RWIS location. Two most commonly used modeling techniques were evaluated, time-series analysis and artificial neural networks. A total of 14 days of data collected by RWIS sensors was used for model calibration and testing. It was found that among the models tested multi-variable SARIMA and ANN are the most competitive techniques in terms of testing results. Multi-variable SARIMA models calibrated for specific forecasting horizons show even more promising results. The uni-variable SARIMA model had excellent quality of fit, but performed poorly in actual forecasting.

5.2 Recommendations for Future Work

This paper has shown some encouraging results using statistical modeling techniques for site-specific local forecasting. These types of techniques are much simpler than traditional large-scale, data-intensive numerical forecasting models. However, many issues still need to be addressed before they can be accepted for field applications. For example, what is the generalization capacity of these models over time and space? That is, will models of similar structure be applicable to other years or other sites? Will the relative performance of these models stay the same across winter seasons and locations? How can we use data from other RWIS stations to improve local forecasting? These are the main issues that need to be addressed in our future research.

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Appendix A

The Input Data: January 22 to February 4, 2007

date (m/d/yyyy h:m)	hour index	Surface Temp (RWIS)	Air Temp (RWIS)	Dew point Temp	Relative Humidity	Pressure	Avg. Wind Speed	Avg. Wind Dir.	Max. Gust Wind Speed	Precip.	Frz Pt.
1/22/2007 0	1	-4.0	-4.0	-7.90	74.00	99.66	14.04	82.00	14.40	0.00	-2.70
1/22/2007 1	2	-5.1	-5.5	-9.00	76.33	99.63	9.96	70.00	12.96	0.00	-1.80
1/22/2007 2	3	-6.1	-7.1	-10.10	78.67	99.61	5.88	58.00	11.52	0.00	-0.90
1/22/2007 3	4	-6.0	-8.6	-11.20	81.00	99.58	1.80	46.00	10.08	0.00	0.00
1/22/2007 4	5	-6.5	-8.7	-11.10	82.00	99.63	6.12	30.67	8.76	0.00	0.00
1/22/2007 5	6	-5.7	-8.7	-11.10	83.00	99.58	8.28	27.00	9.00	0.00	0.00
1/22/2007 6	7	-5.5	-8.6	-10.93	82.33	99.59	6.48	47.00	9.12	0.00	0.00
1/22/2007 7	8	-5.0	-8.7	-11.17	82.00	99.63	5.88	22.67	8.64	0.00	0.00
1/22/2007 8	9	-4.3	-8.8	-11.30	81.00	99.63	7.92	187.00	9.90	0.00	-0.60
1/22/2007 9	10	-3.1	-8.5	-11.10	81.00	99.61	6.84	3.00	7.56	0.00	-1.10
1/22/2007 10	11	-1.4	-7.8	-10.45	80.00	99.54	3.96	13.50	5.22	0.00	-1.30
1/22/2007 11	12	0.3	-6.0	-9.18	77.50	99.41	3.42	174.75	5.94	0.00	-1.70
1/22/2007 12	13	0.7	-4.3	-7.90	75.00	99.28	2.88	336.00	6.66	0.00	-2.10
1/22/2007 13	14	0.9	-3.5	-7.35	74.00	99.22	3.60	28.00	6.12	0.00	-1.80
1/22/2007 14	15	1.0	-3.4	-7.50	72.00	99.19	4.86	330.00	8.46	0.00	0.00
1/22/2007 15	16	-1.3	-3.5	-7.80	72.00	99.21	9.72	318.00	11.52	0.00	0.00
1/22/2007 16	17	-2.2	-4.3	-8.50	72.00	99.21	4.32	345.00	6.48	0.00	0.00
1/22/2007 17	18	-3.3	-4.7	-9.00	71.00	99.24	6.12	324.00	6.48	0.00	0.00
1/22/2007 18	19	-3.5	-5.6	-9.85	71.50	99.28	7.56	331.00	9.00	0.00	0.00
1/22/2007 19	20	-3.7	-5.9	-9.93	72.25	99.27	4.86	202.00	5.76	0.00	0.00
1/22/2007 20	21	-3.5	-6.1	-10.00	73.00	99.26	2.16	73.00	2.52	0.00	0.00
1/22/2007 21	22	-3.5	-5.7	-9.70	73.00	99.24	0.00	0.00	2.52	0.00	0.00
1/22/2007 22	23	-3.8	-5.7	-9.60	73.00	99.23	0.00	0.00	2.88	0.00	0.00
1/22/2007 23	24	-4.0	-5.9	-9.80	73.00	99.21	3.00	286.67	5.28	0.67	-0.33
1/23/2007 0	25	-4.4	-5.6	-9.37	74.00	99.16	1.80	174.00	6.72	0.00	0.00
1/23/2007 1	26	-4.5	-5.5	-9.15	74.50	99.12	6.30	235.50	8.10	0.00	0.00
1/23/2007 2	27	-3.8	-5.8	-9.37	75.00	99.13	7.44	243.00	8.40	0.00	0.00
1/23/2007 3	28	-3.2	-5.4	-8.85	76.00	99.09	4.68	214.00	6.12	0.00	-0.50
1/23/2007 4	29	-2.5	-4.8	-8.20	76.33	99.05	4.68	227.67	6.72	0.00	-1.77
1/23/2007 5	30	-1.9	-4.3	-7.53	77.22	99.02	4.56	219.44	7.00	0.00	-2.54

1/23/2007 6	31	-1.2	-3.7	-6.87	78.11	98.99	4.44	211.22	7.28	0.00	-3.32
1/23/2007 7	32	-0.7	-3.2	-6.20	79.00	98.96	4.32	203.00	7.56	0.00	-4.10
1/23/2007 8	33	0.3	-2.5	-5.50	79.00	98.96	9.00	228.00	12.96	0.00	-4.25
1/23/2007 9	34	1.2	-1.7	-4.85	78.00	98.89	8.10	210.50	10.98	0.00	-3.80
1/23/2007 10	35	2.3	-1.0	-4.40	77.50	98.83	14.94	216.00	17.64	0.00	-3.05
1/23/2007 11	36	1.8	-0.4	-3.90	76.50	98.80	10.26	250.50	18.36	0.00	-2.10
1/23/2007 12	37	1.1	-0.3	-4.10	74.00	98.75	10.80	243.00	15.12	0.00	-0.80
1/23/2007 13	38	1.9	-0.6	-4.50	74.00	98.75	15.12	236.00	23.76	0.00	-2.00
1/23/2007 14	39	1.7	-0.4	-4.03	76.00	98.68	15.72	235.33	20.40	0.00	-1.80
1/23/2007 15	40	1.5	-0.1	-3.93	74.33	98.66	15.36	243.00	19.08	0.00	-1.37
1/23/2007 16	41	1.1	0.0	-4.00	73.00	98.70	18.36	235.00	18.72	0.00	-1.10
1/23/2007 17	42	0.8	-0.4	-4.37	73.33	98.80	17.16	241.17	19.92	0.00	-1.13
1/23/2007 18	43	0.4	-0.8	-4.73	73.67	98.89	15.96	247.33	21.12	0.00	-1.17
1/23/2007 19	44	0.3	-1.2	-5.10	74.00	98.99	14.76	253.50	22.32	0.00	-1.20
1/23/2007 20	45	0.0	-1.3	-5.20	74.00	99.01	16.56	261.00	20.52	0.00	-1.20
1/23/2007 21	46	-0.1	-1.5	-5.35	74.00	99.07	15.84	250.50	23.58	0.00	-1.00
1/23/2007 22	47	-0.2	-1.4	-5.28	74.25	99.11	15.84	253.00	24.75	0.00	-1.00
1/23/2007 23	48	-0.8	-1.4	-5.20	74.50	99.16	15.84	255.50	25.92	0.00	-1.00
1/24/2007 0	49	-0.8	-1.6	-5.40	75.00	99.16	16.20	236.00	20.52	0.00	-1.10
1/24/2007 1	50	-0.6	-1.9	-5.50	75.50	99.19	12.06	246.50	18.54	0.00	-1.10
1/24/2007 2	51	-2.3	-1.7	-5.10	77.00	99.20	12.96	273.00	16.20	0.00	-1.20
1/24/2007 3	52	-2.7	-2.9	-6.60	74.50	99.30	10.80	296.00	14.76	0.00	-1.10
1/24/2007 4	53	-2.4	-3.6	-7.50	74.00	99.35	10.08	292.00	11.52	0.00	0.00
1/24/2007 5	54	-1.9	-4.3	-8.25	73.00	99.42	6.12	294.00	9.54	0.00	-1.00
1/24/2007 6	55	-2.9	-4.4	-8.33	73.67	99.47	8.64	303.33	12.84	0.00	-1.03
1/24/2007 7	56	-3.9	-6.3	-10.07	73.58	99.65	10.71	325.92	13.89	0.00	-1.07
1/24/2007 8	57	-2.9	-8.1	-11.80	73.50	99.83	12.78	348.50	14.94	0.00	-1.10
1/24/2007 9	58	-1.2	-8.1	-11.93	73.00	99.91	9.36	340.33	11.88	0.00	0.00
1/24/2007 10	59	1.8	-7.6	-11.55	72.50	99.88	8.64	190.50	9.36	0.00	0.00
1/24/2007 11	60	2.7	-5.7	-10.60	68.00	99.73	6.12	320.00	8.28	0.00	0.00
1/24/2007 12	61	2.0	-4.9	-10.90	62.00	99.66	13.68	330.00	14.04	0.00	0.00
1/24/2007 13	62	1.4	-5.3	-11.35	61.50	99.63	10.98	332.50	13.32	0.00	0.00
1/24/2007 14	63	-0.2	-5.4	-11.55	61.00	99.62	8.28	350.50	11.70	0.00	0.00
1/24/2007 15	64	-1.8	-6.1	-12.17	61.33	99.67	7.92	334.67	11.52	0.00	0.00
1/24/2007 16	65	-3.1	-6.7	-12.60	62.00	99.73	9.36	339.00	12.12	0.00	0.00

1/24/2007 17	66	-3.4	-7.3	-13.05	62.50	99.71	10.80	177.50	12.78	0.00	0.00
1/24/2007 18	67	-4.3	-7.6	-13.60	61.00	99.81	10.08	347.00	13.68	0.00	0.00
1/24/2007 19	68	-4.5	-8.3	-13.60	65.00	99.85	12.96	344.50	13.50	0.00	-0.55
1/24/2007 20	69	-5.8	-8.7	-13.60	67.00	99.86	6.48	353.00	18.00	1.00	0.00
1/24/2007 21	70	-6.6	-9.6	-14.20	71.00	99.82	8.28	332.00	9.72	0.00	0.00
1/24/2007 22	71	-6.9	-10.0	-14.60	70.00	99.84	9.36	329.00	11.52	0.00	0.00
1/24/2007 23	72	-7.2	-10.5	-15.13	68.67	99.85	6.36	321.33	7.80	0.00	0.00
1/25/2007 0	73	-7.5	-11.0	-15.85	67.50	99.81	7.38	341.00	8.28	0.00	0.00
1/25/2007 1	74	-7.7	-11.4	-16.37	67.00	99.82	8.64	342.67	11.88	0.00	0.00
1/25/2007 2	75	-8.3	-12.0	-17.35	65.50	99.85	11.16	348.50	15.12	0.00	0.00
1/25/2007 3	76	-8.8	-12.6	-17.40	67.50	99.85	12.42	333.50	15.12	0.00	0.00
1/25/2007 4	77	-9.2	-12.9	-17.75	69.00	99.87	10.26	332.00	15.84	0.00	0.00
1/25/2007 5	78	-9.6	-14.0	-18.70	70.00	99.89	10.98	5.50	12.96	0.00	0.00
1/25/2007 6	79	-9.8	-15.1	-19.40	70.00	99.92	10.08	12.00	13.32	0.00	0.00
1/25/2007 7	80	-9.3	-15.3	-19.50	69.50	99.95	7.20	345.50	9.36	0.00	0.00
1/25/2007 8	81	-8.8	-15.3	-19.50	69.00	99.98	7.20	5.00	11.88	0.00	0.00
1/25/2007 9	82	-7.9	-15.3	-18.90	69.00	100.01	7.20	17.00	10.08	0.00	0.00
1/25/2007 10	83	-6.3	-14.7	-19.00	67.50	99.98	8.28	168.50	12.24	0.00	0.00
1/25/2007 11	84	-4.4	-14.3	-18.70	66.00	99.85	15.12	338.00	16.20	0.00	0.00
1/25/2007 12	85	-4.9	-13.6	-18.65	63.00	99.81	20.34	332.50	22.50	0.00	0.00
1/25/2007 13	86	-5.0	-13.9	-19.85	59.50	99.84	22.14	320.50	29.70	0.00	0.00
1/25/2007 14	87	-6.5	-13.2	-20.20	56.00	99.86	27.36	307.00	30.96	0.00	0.00
1/25/2007 15	88	-8.3	-13.7	-20.87	54.33	99.90	24.00	337.00	30.36	0.00	0.00
1/25/2007 16	89	-11.0	-14.0	-21.70	54.00	98.56	20.16	343.00	22.68	0.00	0.00
1/25/2007 17	90	-11.8	-15.0	-22.00	55.33	100.13	14.28	326.33	17.64	0.00	0.00
1/25/2007 18	91	-12.3	-15.4	-22.40	57.00	100.26	19.08	324.00	19.44	0.00	0.00
1/25/2007 19	92	-13.3	-16.1	-22.70	59.00	100.31	8.28	317.00	10.80	0.00	0.00
1/25/2007 20	93	-13.5	-16.7	-22.80	59.00	100.31	11.16	318.00	11.52	0.00	0.00
1/25/2007 21	94	-13.7	-17.0	-22.80	60.50	100.30	10.08	290.00	11.88	0.00	0.00
1/25/2007 22	95	-14.1	-17.3	-22.60	62.33	100.26	7.80	296.67	13.20	0.00	0.00
1/25/2007 23	96	-14.1	-17.3	-22.37	64.33	100.19	5.28	301.33	6.84	0.00	0.00
1/26/2007 0	97	-14.4	-17.6	-22.15	66.50	100.10	4.14	319.00	5.40	0.00	0.00
1/26/2007 1	98	-14.6	-17.4	-21.85	67.50	100.07	3.96	328.50	4.68	0.00	0.00
1/26/2007 2	99	-14.6	-17.5	-21.80	69.00	100.03	5.04	326.00	5.40	0.00	0.00
1/26/2007 3	100	-14.5	-17.5	-21.47	69.67	100.00	5.28	320.33	6.48	0.00	0.00

1/26/2007 4	101	-14.8	-17.5	-21.60	70.00	100.02	6.48	339.00	7.74	0.00	0.00
1/26/2007 5	102	-14.1	-17.7	-22.10	71.00	100.00	3.24	341.00	3.60	0.00	0.00
1/26/2007 6	103	-13.6	-18.2	-22.13	71.00	100.01	4.44	334.00	6.48	0.00	0.00
1/26/2007 7	104	-12.3	-18.1	-21.60	71.00	100.02	3.12	224.00	4.92	0.00	0.00
1/26/2007 8	105	-10.6	-16.9	-20.40	71.00	100.02	3.60	317.00	5.76	0.00	0.00
1/26/2007 9	106	-8.7	-15.9	-19.40	70.00	99.84	4.68	295.67	6.48	0.00	0.00
1/26/2007 10	107	-6.0	-14.0	-16.85	68.00	99.90	5.76	243.50	7.20	0.00	0.00
1/26/2007 11	108	-5.2	-11.4	-15.80	66.00	99.80	6.84	212.50	10.62	0.00	0.00
1/26/2007 12	109	-4.7	-10.2	-15.05	65.50	99.71	4.14	266.50	5.94	0.00	0.00
1/26/2007 13	110	-4.2	-9.9	-14.15	65.00	99.62	4.32	210.50	7.02	0.00	0.00
1/26/2007 14	111	-4.5	-8.3	-13.35	65.00	99.53	6.12	173.50	8.10	0.00	0.00
1/26/2007 15	112	-4.8	-7.8	-12.80	67.00	99.50	8.64	187.00	10.08	0.00	0.00
1/26/2007 16	113	-5.4	-7.9	-12.40	73.00	99.38	12.24	75.00	13.32	1.00	0.00
1/26/2007 17	114	-5.9	-8.2	-12.01	74.56	99.36	10.84	81.33	13.28	0.89	0.00
1/26/2007 18	115	-6.5	-8.5	-11.62	76.11	99.34	9.44	87.67	13.24	0.78	0.00
1/26/2007 19	116	-6.2	-8.8	-11.23	77.67	99.32	8.04	94.00	13.20	0.67	0.00
1/26/2007 20	117	-5.9	-7.9	-9.97	78.83	99.09	13.92	103.00	17.94	0.33	0.00
1/26/2007 21	118	-5.7	-7.0	-8.70	80.00	98.86	19.80	112.00	22.68	0.00	0.00
1/26/2007 22	119	-5.4	-6.5	-8.70	80.50	98.80	22.32	114.00	25.56	0.00	0.00
1/26/2007 23	120	-5.0	-5.9	-8.70	81.00	98.74	24.84	116.00	28.44	0.00	0.00
1/27/2007 0	121	-4.5	-6.0	-7.70	83.00	98.61	16.20	123.00	20.88	1.00	0.00
1/27/2007 1	122	-3.7	-5.3	-6.80	85.00	98.47	14.40	137.00	17.64	1.00	-1.00
1/27/2007 2	123	-3.6	-4.6	-6.25	85.50	98.39	9.36	112.00	13.14	0.00	-1.00
1/27/2007 3	124	-3.0	-3.9	-5.35	86.50	98.29	6.48	117.50	7.92	0.50	-0.50
1/27/2007 4	125	-2.9	-3.2	-4.75	87.50	98.24	9.00	87.50	10.80	0.00	-4.65
1/27/2007 5	126	-2.7	-2.9	-4.30	88.00	98.19	9.00	89.00	10.80	0.00	-2.50
1/27/2007 6	127	-2.5	-2.7	-4.60	89.00	98.26	11.52	86.00	15.48	0.00	-5.30
1/27/2007 7	128	-3.2	-3.2	-7.00	90.00	98.41	6.12	93.00	9.72	0.00	-2.00
1/27/2007 8	129	-3.9	-4.6	-7.18	90.00	98.43	5.04	66.00	8.46	0.25	-1.50
1/27/2007 9	130	-4.0	-6.0	-7.35	90.00	98.46	3.96	39.00	7.20	0.50	-1.00
1/27/2007 10	131	-3.8	-6.1	-7.45	90.00	98.47	4.32	66.50	7.02	0.00	-1.00
1/27/2007 11	132	-3.5	-6.1	-7.13	90.00	98.43	5.04	105.25	6.93	0.00	-1.35
1/27/2007 12	133	-3.0	-6.2	-6.80	90.00	98.40	5.76	144.00	6.84	0.00	-1.70
1/27/2007 13	134	-3.0	-5.5	-6.30	90.00	98.38	6.12	87.00	9.36	0.00	-1.10
1/27/2007 14	135	-3.0	-5.3	-6.45	90.00	98.41	5.94	77.00	9.18	0.00	-1.15

1/27/2007 15	136	-3.5	-5.0	-6.60	90.00	98.44	5.76	67.00	9.00	0.00	-1.20
1/27/2007 16	137	-3.5	-5.3	-6.40	90.00	98.47	3.60	94.00	6.84	1.00	-1.00
1/27/2007 17	138	-3.0	-5.1	-6.15	90.00	98.52	4.68	79.50	6.48	0.50	-1.00
1/27/2007 18	139	-3.5	-4.7	-5.95	90.00	98.53	2.34	122.50	3.60	0.00	-1.00
1/27/2007 19	140	-3.0	-4.6	-4.55	90.00	98.49	3.60	202.00	6.30	0.00	-1.00
1/27/2007 20	141	-2.6	-3.7	-4.18	90.00	98.47	4.38	218.67	7.14	0.00	-1.03
1/27/2007 21	142	-2.2	-2.8	-3.82	90.00	98.46	5.16	235.33	7.98	0.00	-1.07
1/27/2007 22	143	-2.6	-2.0	-3.45	90.00	98.44	5.94	252.00	8.82	0.00	-1.10
1/27/2007 23	144	-2.9	-2.3	-4.17	89.67	98.44	5.04	282.67	7.56	0.00	-1.20
1/28/2007 0	145	-3.1	-3.0	-4.98	89.33	98.49	7.20	307.08	9.27	0.00	-1.20
1/28/2007 1	146	-5.5	-3.7	-5.80	89.00	98.54	9.36	331.50	10.98	0.00	-1.20
1/28/2007 2	147	-6.9	-5.5	-7.90	89.00	98.65	12.06	323.50	14.94	0.00	0.00
1/28/2007 3	148	-7.4	-7.4	-9.33	88.67	98.71	9.36	326.00	11.76	0.00	0.00
1/28/2007 4	149	-6.8	-8.6	-10.20	88.00	98.77	7.20	336.33	8.88	0.00	0.00
1/28/2007 5	150	-6.9	-8.7	-10.90	87.00	98.83	5.40	36.00	7.92	0.00	0.00
1/28/2007 6	151	-6.9	-9.5	-11.55	86.50	98.93	7.38	27.50	8.46	0.00	0.00
1/28/2007 7	152	-6.8	-9.7	-11.53	84.75	98.88	6.03	16.25	8.55	0.00	0.00
1/28/2007 8	153	-5.7	-9.9	-11.50	83.00	98.82	4.68	5.00	8.64	0.00	0.00
1/28/2007 9	154	-4.5	-9.8	-11.53	83.00	98.82	4.32	5.75	8.82	0.00	-0.85
1/28/2007 10	155	-3.4	-9.6	-11.55	83.00	98.82	3.96	6.50	9.00	0.00	-1.70
1/28/2007 11	156	-2.2	-9.5	-11.58	83.00	98.81	3.60	7.25	9.18	0.00	-2.55
1/28/2007 12	157	-2.5	-9.3	-11.60	83.00	98.81	3.24	8.00	9.36	0.00	-3.40
1/28/2007 13	158	-3.3	-9.5	-11.50	82.00	98.85	6.48	353.00	10.08	1.00	-2.70
1/28/2007 14	159	-4.0	-9.3	-11.60	81.50	98.87	8.64	354.00	10.62	0.50	-1.85
1/28/2007 15	160	-5.0	-9.1	-11.70	81.00	98.89	10.80	355.00	11.16	0.00	-1.00
1/28/2007 16	161	-6.4	-9.4	-12.30	80.50	98.97	10.44	339.00	13.86	0.50	-0.60
1/28/2007 17	162	-7.0	-10.1	-13.05	80.00	99.07	13.32	330.50	15.30	0.00	0.00
1/28/2007 18	163	-7.2	-10.4	-13.52	79.60	99.13	12.17	327.80	14.04	0.00	0.00
1/28/2007 19	164	-7.4	-10.4	-13.99	79.20	99.20	11.02	325.10	12.78	0.00	0.00
1/28/2007 20	165	-7.6	-10.3	-14.46	78.80	99.26	9.86	322.40	11.52	0.00	0.00
1/28/2007 21	166	-7.8	-10.3	-14.93	78.40	99.33	8.71	319.70	10.26	0.00	0.00
1/28/2007 22	167	-9.1	-10.2	-15.40	78.00	99.39	7.56	317.00	9.00	0.00	0.00
1/28/2007 23	168	-10.3	-11.5	-15.70	78.00	99.42	9.27	318.00	11.70	0.00	0.00
1/29/2007 0	169	-10.9	-12.7	-16.00	78.00	99.46	10.98	319.00	14.40	0.00	0.00
1/29/2007 1	170	-11.8	-13.3	-16.60	78.00	99.54	13.50	316.00	14.40	0.00	0.00

1/29/2007 2	171	-12.2	-14.1	-17.30	78.00	99.58	7.56	323.33	10.08	0.00	0.00
1/29/2007 3	172	-12.6	-14.9	-17.95	78.00	99.56	1.98	161.50	5.40	0.00	0.00
1/29/2007 4	173	-11.6	-15.3	-18.20	78.00	99.60	3.36	197.33	5.52	0.00	0.00
1/29/2007 5	174	-10.9	-14.9	-17.40	78.00	99.62	5.76	272.00	9.18	0.00	0.00
1/29/2007 6	175	-8.8	-14.6	-14.00	76.00	99.52	9.18	275.00	11.34	0.00	0.00
1/29/2007 7	176	-6.7	-13.1	-13.44	75.80	99.49	10.66	274.80	13.39	0.00	-0.20
1/29/2007 8	177	-4.5	-11.5	-12.88	75.60	99.47	12.13	274.60	15.44	0.00	-0.40
1/29/2007 9	178	-2.4	-10.0	-12.32	75.40	99.45	13.61	274.40	17.50	0.00	-0.60
1/29/2007 10	179	-0.3	-8.4	-11.76	75.20	99.42	15.08	274.20	19.55	0.00	-0.80
1/29/2007 11	180	-1.7	-6.9	-11.20	75.00	99.40	16.56	274.00	21.60	0.00	-1.00
1/29/2007 12	181	-0.5	-7.6	-10.30	74.00	99.32	16.92	279.00	21.60	0.00	-1.00
1/29/2007 13	182	-0.9	-6.2	-9.57	74.67	99.32	13.32	256.67	18.00	0.00	-0.67
1/29/2007 14	183	-1.0	-5.9	-9.47	74.67	99.31	14.16	259.00	18.60	0.00	-1.00
1/29/2007 15	184	-2.6	-5.6	-9.73	73.33	99.30	17.64	260.67	26.40	0.00	-0.67
1/29/2007 16	185	-3.6	-5.8	-10.10	72.00	99.32	12.60	272.00	20.70	0.00	0.00
1/29/2007 17	186	-4.4	-6.2	-10.40	72.00	99.38	12.84	248.00	17.64	0.00	0.00
1/29/2007 18	187	-4.9	-6.6	-11.45	73.50	99.49	11.52	274.50	13.14	0.00	0.00
1/29/2007 19	188	-5.5	-7.2	-11.76	74.13	99.50	9.68	283.63	10.98	0.00	0.00
1/29/2007 20	189	-6.0	-7.8	-12.08	74.75	99.52	7.83	292.75	8.82	0.00	0.00
1/29/2007 21	190	-6.8	-8.3	-12.39	75.38	99.54	5.99	301.88	6.66	0.00	0.00
1/29/2007 22	191	-7.5	-8.9	-12.70	76.00	99.56	4.14	311.00	4.50	0.00	0.00
1/29/2007 23	192	-7.7	-9.5	-13.20	76.00	99.53	3.60	358.00	3.96	0.00	0.00
1/30/2007 0	193	-8.4	-10.2	-13.60	77.00	99.50	2.16	173.00	3.42	0.00	0.00
1/30/2007 1	194	-9.2	-10.9	-14.33	77.33	99.46	2.64	11.67	3.24	0.00	0.00
1/30/2007 2	195	-8.9	-11.5	-14.37	78.00	99.46	3.36	50.67	6.00	0.00	0.00
1/30/2007 3	196	-8.5	-11.0	-13.70	78.00	99.49	3.42	85.50	7.38	0.00	0.00
1/30/2007 4	197	-8.8	-10.6	-14.30	78.00	99.46	0.00	0.00	2.88	0.00	0.00
1/30/2007 5	198	-8.0	-11.4	-15.00	78.00	99.43	0.00	0.00	3.96	0.00	0.00
1/30/2007 6	199	-8.7	-11.9	-15.60	78.00	99.45	8.28	57.00	10.44	1.00	0.00
1/30/2007 7	200	-8.5	-12.9	-15.90	79.00	99.46	7.38	30.00	10.44	1.00	0.00
1/30/2007 8	201	-8.0	-13.0	-15.50	79.00	99.46	3.06	35.00	9.36	0.00	0.00
1/30/2007 9	202	-5.6	-12.6	-13.70	78.00	99.33	6.48	8.00	6.48	1.00	0.00
1/30/2007 10	203	-4.9	-10.3	-12.60	78.50	99.31	5.22	19.00	6.84	1.00	-0.65
1/30/2007 11	204	-3.0	-9.0	-10.95	79.00	99.20	4.68	15.00	7.38	1.00	-1.05
1/30/2007 12	205	-2.5	-7.4	-9.60	79.50	99.11	3.96	38.50	5.94	1.00	-1.00

1/30/2007 13	206	-2.1	-6.4	-9.13	80.00	99.08	3.00	136.00	7.20	0.67	-1.80
1/30/2007 14	207	-2.9	-6.0	-8.75	80.00	99.07	3.60	205.00	4.32	0.00	-1.55
1/30/2007 15	208	-4.0	-6.5	-9.25	79.50	99.13	2.52	175.50	5.22	0.00	-1.35
1/30/2007 16	209	-5.1	-6.4	-10.30	78.50	99.25	1.26	26.00	1.98	0.00	-1.65
1/30/2007 17	210	-6.2	-7.3	-11.08	79.75	99.34	4.41	86.75	6.03	0.00	-0.83
1/30/2007 18	211	-6.7	-8.3	-11.85	81.00	99.44	7.56	147.50	10.08	0.00	0.00
1/30/2007 19	212	-7.1	-8.5	-11.96	81.21	99.45	7.61	166.64	10.29	0.00	0.00
1/30/2007 20	213	-7.6	-8.8	-12.06	81.43	99.47	7.66	185.79	10.49	0.00	0.00
1/30/2007 21	214	-8.0	-9.1	-12.17	81.64	99.49	7.71	204.93	10.70	0.00	0.00
1/30/2007 22	215	-8.5	-9.3	-12.28	81.86	99.50	7.77	224.07	10.90	0.00	0.00
1/30/2007 23	216	-8.9	-9.6	-12.39	82.07	99.52	7.82	243.21	11.11	0.00	0.00
1/31/2007 0	217	-9.4	-9.9	-12.49	82.29	99.54	7.87	262.36	11.31	0.00	0.00
1/31/2007 1	218	-9.6	-10.2	-12.60	82.50	99.56	7.92	281.50	11.52	0.00	0.00
1/31/2007 2	219	-9.5	-10.5	-13.05	81.50	99.56	7.56	257.50	9.72	0.00	0.00
1/31/2007 3	220	-9.1	-10.7	-13.20	80.00	99.52	4.68	239.00	7.56	0.00	0.00
1/31/2007 4	221	-7.0	-10.2	-12.03	80.67	99.49	9.72	233.67	13.20	0.00	0.00
1/31/2007 5	222	-6.4	-8.2	-10.80	81.00	99.46	10.80	237.00	12.96	0.00	0.00
1/31/2007 6	223	-5.7	-7.9	-10.20	79.50	99.45	14.40	220.50	16.92	0.00	0.00
1/31/2007 7	224	-4.2	-7.1	-9.73	78.33	99.48	15.12	238.67	20.52	0.00	0.00
1/31/2007 8	225	-2.8	-6.5	-9.29	77.17	99.49	22.77	243.83	26.64	0.00	-1.48
1/31/2007 9	226	-0.3	-6.0	-8.85	76.00	99.50	30.42	249.00	32.76	0.00	-2.95
1/31/2007 10	227	0.8	-4.9	-8.80	75.00	99.49	23.76	262.00	29.16	0.00	-1.70
1/31/2007 11	228	1.7	-4.9	-8.40	74.67	99.46	25.68	260.67	31.44	0.00	-1.13
1/31/2007 12	229	2.4	-4.6	-8.05	73.50	99.45	20.34	267.50	30.06	0.00	-0.40
1/31/2007 13	230	1.4	-3.9	-7.90	72.67	99.42	18.00	266.00	28.08	0.00	0.00
1/31/2007 14	231	0.4	-4.1	-8.33	72.33	99.44	19.68	267.67	23.28	0.00	0.00
1/31/2007 15	232	-1.8	-4.0	-8.83	70.67	99.47	15.72	247.33	21.24	0.00	0.00
1/31/2007 16	233	-3.3	-5.3	-10.03	70.00	99.54	13.44	252.67	21.72	0.00	0.00
1/31/2007 17	234	-3.7	-6.1	-10.55	70.00	99.65	7.56	250.50	14.40	0.00	0.00
1/31/2007 18	235	-4.3	-5.9	-10.67	70.00	99.64	9.60	235.00	15.72	0.00	0.00
1/31/2007 19	236	-4.9	-6.3	-10.86	70.75	99.60	12.81	234.25	18.57	0.00	0.00
1/31/2007 20	237	-5.0	-6.7	-11.05	71.50	99.57	16.02	233.50	21.42	0.00	0.00
1/31/2007 21	238	-5.2	-6.7	-10.96	71.75	99.53	18.51	236.25	23.07	0.00	0.00
1/31/2007 22	239	-5.1	-6.8	-10.87	72.00	99.50	21.00	239.00	24.72	0.00	0.00
1/31/2007 23	240	-5.0	-6.7	-11.00	71.00	99.40	21.96	242.00	27.36	0.00	0.00

2/1/2007 0	241	-4.9	-6.7	-11.00	70.50	99.37	15.84	231.50	21.78	0.00	0.00
2/1/2007 1	242	-4.9	-6.6	-11.07	69.67	99.34	15.60	230.00	18.24	0.00	0.00
2/1/2007 2	243	-4.9	-6.4	-11.10	68.00	99.31	13.80	223.33	16.68	0.00	0.00
2/1/2007 3	244	-5.1	-6.4	-12.13	64.00	99.29	20.52	241.67	23.64	0.00	0.00
2/1/2007 4	245	-4.6	-6.9	-12.67	63.00	99.27	12.24	243.67	16.20	0.00	0.00
2/1/2007 5	246	-4.5	-6.7	-12.23	63.67	99.22	10.32	229.00	15.36	0.00	0.00
2/1/2007 6	247	-3.4	-6.7	-9.40	68.00	99.10	10.08	219.00	11.16	0.00	0.00
2/1/2007 7	248	-2.3	-5.9	-9.38	67.50	99.09	9.48	223.83	12.42	0.00	0.00
2/1/2007 8	249	-1.3	-5.2	-9.37	67.00	99.08	8.88	228.67	13.68	0.00	0.00
2/1/2007 9	250	0.1	-4.4	-9.35	66.50	99.07	8.28	233.50	14.94	0.00	0.00
2/1/2007 10	251	1.8	-3.6	-9.03	63.33	99.01	10.32	224.33	15.60	0.00	0.00
2/1/2007 11	252	3.0	-2.5	-8.43	62.00	98.93	13.56	211.00	19.08	0.00	0.00
2/1/2007 12	253	3.9	-1.9	-7.57	64.00	98.85	17.04	211.67	23.88	0.00	0.00
2/1/2007 13	254	3.8	-1.5	-6.55	67.00	98.77	22.32	212.00	28.26	0.00	0.00
2/1/2007 14	255	2.3	-1.4	-6.60	66.50	98.78	17.82	218.00	23.04	0.00	0.00
2/1/2007 15	256	-0.2	-1.0	-6.50	67.00	98.80	19.68	221.67	24.96	0.00	0.00
2/1/2007 16	257	-0.8	-2.1	-6.80	72.00	98.89	12.60	227.00	15.48	0.00	0.00
2/1/2007 17	258	-1.4	-2.3	-6.80	72.25	98.90	13.23	226.25	15.48	0.00	-0.50
2/1/2007 18	259	-1.6	-2.6	-6.80	72.50	98.91	13.86	225.50	15.48	0.00	-1.00
2/1/2007 19	260	-2.0	-2.7	-7.10	73.00	98.91	16.20	230.00	19.08	0.00	-1.00
2/1/2007 20	261	-1.8	-3.1	-7.20	74.00	98.91	6.84	237.00	9.72	0.00	-1.00
2/1/2007 21	262	-1.6	-3.2	-7.25	74.00	98.79	6.75	236.75	10.35	0.00	-1.00
2/1/2007 22	263	-1.5	-3.4	-7.30	74.00	98.68	6.66	236.50	10.98	0.00	-1.00
2/1/2007 23	264	-1.9	-3.6	-7.80	74.00	98.84	7.92	260.00	10.80	0.00	-1.00
2/2/2007 0	265	-2.1	-3.9	-7.75	74.00	98.79	7.02	254.00	9.18	0.00	-1.00
2/2/2007 1	266	-2.5	-4.1	-8.03	74.00	98.76	5.16	252.67	7.68	0.00	-1.03
2/2/2007 2	267	-2.4	-4.3	-8.10	74.00	98.65	0.00	0.00	2.16	0.00	-1.20
2/2/2007 3	268	-2.3	-4.4	-8.00	74.50	98.65	1.80	114.00	3.78	0.00	-1.10
2/2/2007 4	269	-1.7	-4.4	-7.90	75.00	98.66	3.60	228.00	5.40	0.00	-1.00
2/2/2007 5	270	-1.3	-3.9	-7.40	75.00	98.62	3.96	216.00	5.04	0.00	-1.00
2/2/2007 6	271	-1.2	-3.8	-7.63	74.00	98.59	3.00	242.00	5.64	0.00	-1.00
2/2/2007 7	272	-0.8	-3.9	-7.65	73.50	98.53	3.96	222.00	9.72	0.00	-0.50
2/2/2007 8	273	-0.3	-3.4	-7.30	72.00	98.51	7.20	198.00	9.00	0.00	0.00
2/2/2007 9	274	1.5	-3.3	-7.65	70.00	98.45	10.08	214.50	14.04	0.00	0.00
2/2/2007 10	275	2.5	-2.6	-7.90	64.50	98.36	9.18	215.00	12.06	0.00	0.00

2/2/2007 11	276	3.6	-1.9	-8.07	61.67	98.29	6.36	226.00	15.12	0.00	0.00
2/2/2007 12	277	3.8	-1.5	-8.10	59.33	98.13	12.48	228.00	21.60	0.00	0.00
2/2/2007 13	278	2.5	-1.6	-7.90	61.67	98.07	9.36	235.67	15.12	0.00	0.00
2/2/2007 14	279	1.7	-1.6	-7.75	62.50	98.00	12.60	236.50	15.48	0.00	0.00
2/2/2007 15	280	0.5	-1.8	-7.85	63.50	98.04	13.32	224.00	18.36	0.00	0.00
2/2/2007 16	281	0.2	-2.2	-7.40	67.00	98.08	6.48	233.00	18.00	0.00	0.00
2/2/2007 17	282	-1.2	-2.1	-7.40	70.00	98.18	15.48	239.00	20.52	0.00	0.00
2/2/2007 18	283	-2.2	-2.9	-7.90	71.00	98.24	18.54	256.50	24.12	0.00	-0.80
2/2/2007 19	284	-3.5	-4.2	-9.83	67.67	98.36	21.00	257.67	28.32	0.00	-0.33
2/2/2007 20	285	-4.7	-5.8	-11.75	66.50	98.52	28.44	285.00	33.30	0.00	0.00
2/2/2007 21	286	-6.3	-7.7	-12.90	67.00	98.69	19.80	272.67	31.20	0.00	0.00
2/2/2007 22	287	-7.1	-8.8	-14.87	62.67	98.81	19.08	265.67	29.52	0.00	0.00
2/2/2007 23	288	-7.8	-9.4	-15.18	63.08	98.87	20.16	261.08	29.79	0.00	0.00
2/3/2007 0	289	-8.3	-10.0	-15.50	63.50	98.93	21.24	256.50	30.06	0.00	0.00
2/3/2007 1	290	-8.6	-10.1	-15.50	65.00	98.99	18.36	246.00	24.66	0.00	0.00
2/3/2007 2	291	-8.8	-10.5	-15.35	66.00	99.02	14.94	237.00	18.54	0.00	0.00
2/3/2007 3	292	-9.6	-10.3	-15.60	69.00	99.05	17.28	237.00	20.16	0.00	0.00
2/3/2007 4	293	-9.7	-11.3	-15.80	70.00	99.10	15.84	231.00	21.24	0.00	0.00
2/3/2007 5	294	-10.0	-11.5	-15.80	70.33	99.10	14.04	234.00	20.76	0.00	0.00
2/3/2007 6	295	-10.1	-11.7	-16.60	71.00	99.17	12.60	234.00	22.32	0.00	0.00
2/3/2007 7	296	-8.3	-12.5	-15.90	71.00	99.16	12.60	232.00	17.64	0.00	0.00
2/3/2007 8	297	-6.3	-11.8	-15.50	70.00	99.14	12.24	233.00	15.84	0.00	0.00
2/3/2007 9	298	-3.8	-10.7	-14.35	65.00	99.05	19.08	232.50	25.38	0.00	0.00
2/3/2007 10	299	-1.2	-9.2	-14.33	61.33	98.99	20.22	228.92	26.37	0.00	0.00
2/3/2007 11	300	0.7	-7.8	-14.30	57.67	98.93	21.36	225.33	27.36	0.00	0.00
2/3/2007 12	301	0.4	-7.1	-14.60	53.00	98.82	23.04	235.50	30.24	0.00	0.00
2/3/2007 13	302	-0.5	-6.5	-13.80	54.50	98.73	23.76	220.00	25.74	0.00	0.00
2/3/2007 14	303	-1.7	-6.4	-13.10	60.00	98.73	20.16	236.00	25.74	0.00	0.00
2/3/2007 15	304	-4.0	-7.1	-13.00	62.00	98.74	27.36	213.00	27.36	0.00	0.00
2/3/2007 16	305	-6.1	-7.6	-12.93	67.00	98.83	24.72	229.67	31.56	0.33	-0.90
2/3/2007 17	306	-7.2	-8.4	-13.30	68.50	98.98	20.88	243.00	31.68	0.00	0.00
2/3/2007 18	307	-7.7	-8.9	-14.20	65.00	99.06	23.76	238.00	29.34	0.00	0.00
2/3/2007 19	308	-8.7	-9.2	-15.20	64.33	99.17	32.28	249.00	39.24	0.00	0.00
2/3/2007 20	309	-9.6	-10.1	-15.80	64.67	99.27	26.40	251.50	39.96	0.00	0.00
2/3/2007 21	310	-10.1	-11.0	-16.40	65.00	99.36	20.52	254.00	40.68	0.00	0.00

2/3/2007 22	311	-10.5	-11.4	-16.80	64.50	99.41	27.00	248.50	32.76	0.00	0.00
2/3/2007 23	312	-10.8	-11.9	-17.43	64.00	99.49	27.48	252.33	34.68	0.00	0.00
2/4/2007 0	313	-11.7	-12.3	-17.60	67.00	99.55	23.04	236.00	28.08	0.00	0.00
2/4/2007 1	314	-12.6	-13.1	-17.90	68.00	99.58	23.76	242.00	28.62	0.00	0.00
2/4/2007 2	315	-13.0	-13.7	-18.25	69.00	99.63	19.08	238.50	27.00	0.00	0.00
2/4/2007 3	316	-13.3	-14.1	-18.63	69.33	99.65	24.48	245.00	32.28	0.00	0.00
2/4/2007 4	317	-13.3	-14.7	-19.20	69.00	99.68	28.80	237.00	30.96	0.00	0.00
2/4/2007 5	318	-13.2	-15.0	-19.40	69.00	99.70	26.28	236.00	28.44	0.00	0.00
2/4/2007 6	319	-13.1	-15.2	-19.60	68.67	99.71	22.56	243.00	32.28	0.00	0.00
2/4/2007 7	320	-12.1	-15.4	-19.80	68.00	99.73	22.32	250.00	27.00	0.00	0.00
2/4/2007 8	321	-10.1	-15.1	-19.45	67.00	99.72	23.94	241.00	28.44	0.00	0.00
2/4/2007 9	322	-7.5	-14.6	-19.40	65.33	99.67	20.88	251.67	34.68	0.00	0.00
2/4/2007 10	323	-6.1	-14.4	-19.63	62.33	99.63	24.60	257.33	34.68	0.00	0.00
2/4/2007 11	324	-5.3	-13.9	-19.83	60.00	99.59	21.72	261.33	34.32	0.00	0.00
2/4/2007 12	325	-5.9	-13.6	-19.90	58.50	99.56	32.76	258.00	41.40	0.00	0.00
2/4/2007 13	326	-7.1	-13.7	-19.80	59.00	99.56	19.68	257.33	31.68	0.00	0.00
2/4/2007 14	327	-7.5	-13.9	-19.55	62.00	99.61	29.16	247.50	36.72	0.00	0.00
2/4/2007 15	328	-10.0	-14.0	-20.50	60.00	99.74	24.48	256.00	34.92	0.00	0.00
2/4/2007 16	329	-10.6	-14.6	-20.80	59.00	99.76	25.20	265.00	30.60	0.00	0.00
2/4/2007 17	330	-11.6	-14.8	-21.40	58.00	99.83	27.72	254.00	39.96	0.00	0.00
2/4/2007 18	331	-12.5	-15.2	-20.90	60.00	99.92	26.64	249.00	30.24	0.00	0.00
2/4/2007 19	332	-12.7	-15.2	-21.15	60.00	99.96	17.82	254.50	28.98	0.00	0.00
2/4/2007 20	333	-12.7	-15.3	-21.10	60.00	99.96	18.54	257.00	33.48	0.00	0.00
2/4/2007 21	334	-12.6	-15.2	-21.05	60.00	99.95	20.88	254.00	32.04	0.00	0.00
2/4/2007 22	335	-13.3	-15.3	-20.90	61.00	99.90	23.40	242.00	30.24	0.00	0.00