Real-Time Road Ice Prediction and Its Improvement in Accuracy Through a Self-Learning Process

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In winter road maintenance, it is important for highway engineers and authorities to know where and when road surface temperature is to fall below freezing and whether road surfaces will remain dry or icy. To provide this information, several numerical models have been developed in the last decade. However, the accuracy of model prediction in real-time application largely depends on the accuracy of forecast inputs (such as air temperature, dew point, wind speed, cloud type, and cloud amount), which are typically supplied by meteorologists. The experience and skills of the meteorologists are critical in some circumstances for the models to provide useful and reliable output. There is little doubt that such experience and skills vary individually within a group of meteorologists. To remedy model prediction errors resulting from input errors, a self-learning process is developed. The magnitude of error in real-time model input is investigated by comparing forecast input to actual measurements and observations, and the effect of input error on model prediction is demonstrated. A variety of methods, including self-adjustment and self-quality-control mechanisms, are introduced in this paper to show improvements of a numerical model in 24-hr forecasts and 3-to-6-hr nowcasts of road surface temperature.

Since the early 1980s, numerical prediction of road surface temperature for winter road maintenance has become more and more popular and has been accepted as a useful tool to determine where and when ice or frost is likely to occur (*1–5*). Such information enables highway engineers or authorities to salt or grit potentially freezing roads at the right time to minimize the cost of salting/gritting operations and possible damage to the environment. To achieve maximum benefits, the accuracy and reliability of temperature prediction is vitally important.

It has been known that nearly all input for a site-specific road ice prediction, produced by either human forecasters or mesoscale models, unavoidably has large or small departures from real conditions. As a consequence, the error in the input causes systematic or non-systematic distortion in road ice predication. Even in the case of automatic nowcasting (*5*), self-generated input by the model contains a degree of error. Although many statistical and dynamic ways (e.g., Kalman filter) exist to diagnose and adjust the error of numerical predictions, the principle of "simplicity is beauty" should be adopted in road ice prediction. This view is supported by three considerations. First, computing time and space are often limited for a local user of a model. Second, fast updating of prediction is desired in certain circumstances (e.g., when weather conditions are charging significantly). Third, only a few fundamental meteorological variables are measured at an automatic roadside weather station. These limitations or requirements mean that using some sophisticated error-correction schemes (e.g., Kalman filter) for this particular problem may not be practicable. A desirable method of road ice prediction is one that requires less computing time, computer storage space, and human intervention; one that is better understood by users; and one that is effective in removing errors in real time.

In the past, a method of simple template has been proved to be useful to remove systematic errors (*6,7*).

However, the effectiveness of the method is restricted in some circumstances (e.g., when the error is systematic or weather conditions do not change rapidly). To overcome this drawback, a new attempt is made in this paper to search for simple and effective methods to reduce model prediction errors in real time.

Data Collection

24-hr Forecast

Real-time input (in 24 hr) is usually provided on-line by local meteorologists and stored in archives. Therefore, a number of stations and days of real-time or realistic inputs (together with measurements of road surface temperature) have been successfully collected and extracted. The largest data set was obtained at Chapman's Hill (site code: WN001) on the M5 near Birmingham, England, from December 1, 1988, to March 12, 1989, and was derived from hard copy (printout). This site has been used as a model and sensor testing site since 1988. It is also a typical motorway forecast site. The data cover 65 days with forecasts of air temperature, dew point, wind speed, cloud amount, cloud type, and precipitation in 3-hr intervals, and sensor measurements of surface temperature in 1-hr intervals.

It is understandable that forecast input at one site may contain human errors by the group of forecast providers responsible for the site. Such errors in real-time input are likely to differ from one group (or site) to another in both magnitude and style. Therefore, an error-correcting method that is valid for one site may not work at another site. For this reason, efforts have been made to recover data from sites other than Chapman's Hill. In the Netherlands, 2 to 9 days' data were reestablished at four sites (GM004, GN001, HB008, and NW021). Another 2 to 3 days' data were recovered at three sites (RL002, RL004, and RL006) in Norway. These sites are located in different geographical and climatic regions with different topography and road construction, meteorologists' skills and experience also differ from site to site. The sites are considered to provide a reasonable database for the validation of methods developed in this paper.

Nowcasts

It has been shown elsewhere (5) that the accuracy of a self-integrated and automatic road ice nowcasting model deteriorates when weather conditions change dramatically. It is expected that the model should be able to monitor the change and make necessary adjustment to subsequent nowcasts without human intervention. For testing of the nowcasting model, a series of data was collected at an Austrian site (NO001) on the A21 near Vienna for the period from January 10, 1996, to April 20, 1996 (72 days). As a by-validation, another site (SM001) on a flat plain in northern Italy between Bologna and Ferrara was also used for the study. Its data cover 53 days, from January 18, 1994, to March 17, 1994.

Midnight Adjustment

In the so-called template method (6,7), hourly model predictions in a specific day are corrected by the mean hourly error of predictions in previous days. Because weather conditions and a human forecasters' errors are unlikely to be the same or even similar for more than 1 day, this method is only useful to remove systematic or regular errors when weather conditions remain unchanged and input is provided by the same forecaster. In reality, forecaster error and weather condition change can become significant within a 12-hr period, usually starting at noon. In these cases, the template method contains too much old and useless information from some days ago; new and fresher information about model prediction error becomes increasingly important. On the other hand, accurate prediction of minimum temperature, which usually occurs at or shortly before dawn, is one of the most important parameters for winter road maintenance. For these reasons, a method called midnight adjustment is developed.

In this method, the model is fed original real-time input and run for 24 hr until noon of the next day. After 12 hr model performance is checked at midnight and the original forecasts are adjusted from 0100 to 1200. The algorithm of the method can be simply described by two equations:

$$\overline{E}_m = \frac{1}{n}\sum_{i=1}^{n}\left(F_i - A_i\right) \tag{1}$$

and

$$\hat{F}_j = F_j - \overline{E}_m, \quad j = 1,2,\ldots, 12\,(\text{hour}) \tag{2}$$

where

$\overline{E}_m$ = averaged model error in the previous n hours before 0100,
F_i and A_i = respectively forecast and actual road surface temperatures at hour i,
F_j = original model forecast for the period from 0100 to 1200, and
$\hat{F}_j$ = the forecast after midnight adjustment.

To get rid of "memory" that may be too old and may have a negative influence on the effectiveness of the adjustment, n is determined to be 3, that is, the error is averaged from 2200 to 0000.

TABLE 1 Comparison of Adjusted and Nonadjusted Forecasts of All Nights (Chapman's Hill, 1988–1989, 65 days)

	Noon to noon (24 hours)				After mid-night (12 hours)			
	Overall		Minimum		Overall		Minimum	
	Bias	RMS	Bias	RMS	Bias	RMS	Bias	RMS
Adjusted	0.12	1.39	-0.08	1.34	-0.01	1.39	-0.10	1.32
Not adjusted	0.05	1.47	-0.16	1.50	-0.14	1.54	-0.16	1.49
Improvement	-0.07	0.08	0.08	0.16	0.13	0.15	0.06	0.17

TABLE 2 Comparison of Adjusted and Nonadjusted Forecasts of Marginal Nights (Chapman's Hill, 1988–1989, 15 days)

	Noon to noon (24 hours)				After mid-night (12 hours)			
	Overall		Minimum		Overall		Minimum	
	Bias	RMS	Bias	RMS	Bias	RMS	Bias	RMS
Adjusted	0.09	1.45	0.05	0.90	0.20	1.48	0.05	0.90
Not adjusted	-0.08	1.45	-0.21	1.11	-0.13	1.48	-0.18	1.15
Improvement	-0.01	0.0	0.16	0.21	-0.07	0.0	0.13	0.25

In Table 1, the results of the application of the method to all nights at Chapman's Hill are compared with the results of unadjusted forecasts. The comparison was made on every hour available in all days and minimum temperature forecasts in two periods: noon to noon and midnight to noon. In the table, a positive sign shows the reduction of error by the adjustment and a negative sign shows its increase of error. The table shows that for a 24-hr comparison, the adjustment's slight reduction of overall root mean square (RMS) error is accompanied by a small increase in its bias. Apart from this, an improvement of around 0.1°C is generally seen in the comparison. Results of similar comparisons of marginal nights when minimum surface temperature was in the range of −1°C to +1°C are shown in Table 2. As the table indicates, the error of minimum temperature forecast with midnight error adjustment was significantly reduced by 0.13°C to 0.25°C for the marginal nights.

The improvements in accuracy of overall and minimum temperature predictions are also seen at sites in Holland (GM004, GN001, HB008, and NW021) and Norway (RL002, RL004, and RL006). Tables 3 and 4 show the improvement of minimum temperature prediction at these sites. The reduction of RMS error in minimum temperature forecast by the method is generally

TABLE 3 Comparison of Adjusted and Nonadjusted Minimum Temperature Predictions (Holland)

	GM004		GN001		HB008		NW021	
	Bias	RMS	Bias	RMS	Bias	RMS	Bias	RMS
Adjusted	0.28	1.43	0.04	1.39	-0.25	1.59	0.35	0.49
Not adjusted	0.13	1.81	-0.47	1.86	-0.57	2.13	0.45	0.64
Improvement	-0.15	0.38	0.43	0.47	0.32	0.54	0.10	0.15

TABLE 4 Comparison of Adjusted and Nonadjusted Minimum Temperature Predictions (Norway)

	RL002		RL004		RL006	
	Bias	RMS	Bias	RMS	Bias	RMS
Adjusted	0.85	0.85	0.95	1.10	0.63	0.69
Not adjusted	0.95	0.96	1.40	1.40	0.57	0.65
Improvement	0.10	0.09	0.05	0.30	-0.06	-0.04

seen at these sites. The largest reduction is 0.54°C at HB008. Although the number of samples (or days) at each site is limited, the results are encouraging, and the average improvement at these sites is 0.2°C in bias and 0.36°C in RMS error.

Although the results are positive, the application of midnight adjustment does not mean that improvement can be made on every night and under all conditions. Figure 1 displays the daily variation of improvement by the technique for all hours over during 65 days at Chapman's Hill. The same variation for marginal nights is demonstrated in Figure 2. In these figures, positive (above zero bar) means improvement of forecast accuracy, while whereas negative means deterioration. It is seen from the figures that although positive improvement dominates, a much worse forecast can be made with the adjustment in some circumstances. One example is day 48 or December 12, 1989, in Figure 1, and day 11 or December 12, 1989, in Figure 2. Analysis of the first example reveals that in the input data, both air temperature (1.5°C) and cloud amount (0 octa) forecasts were significantly underestimated at 2100, compared with actual (4.0°C and 4 octas). In contrast, both air temperature and cloud amount were then overestimated after midnight. The consequence of this mistake in the input is a large negative error (and thus positive adjustment) of road surface temperature prediction. This error, caused by underestimation of air temperature and cloud amount in the period of 2200 to 0000, was passed on and added to the erroneous predictions resulting from overestimation in the period after midnight. Therefore, the prediction after midnight deteriorated substantially. This example shows the principal limitation of the midnight adjustment technique.

Self-Learning in Nowcasting

One of the most important features of automated and accurate nowcasting is the generation of short-term forecasts without human intervention. In such nowcasting, the input of air temperature, dew point, wind speed, cloud type and amount, and precipitation are all generated within the model itself. This feature can save costs by minimizing provision of human forecasts and has the potential to provide "cheap, cheerful and accurate" (*8*) forecasts in meteorological applications. To check and improve the quality of road ice nowcasting and to retain this important feature of automation, a scheme of self-quality-control is introduced into the icebreak model.

Air temperature is one of the most dominant factors controlling the variation in (and prediction of) road surface temperature. Therefore, model-generated forecasts of air temperature become a natural target for improvement. In the scheme, the model learns from historical data consisting of sensor measurements and nowcasts. Combined with its knowledge of current time, sunshine, and humidity, the model decides if an error correction is necessary. The fundamental decision rules are presented

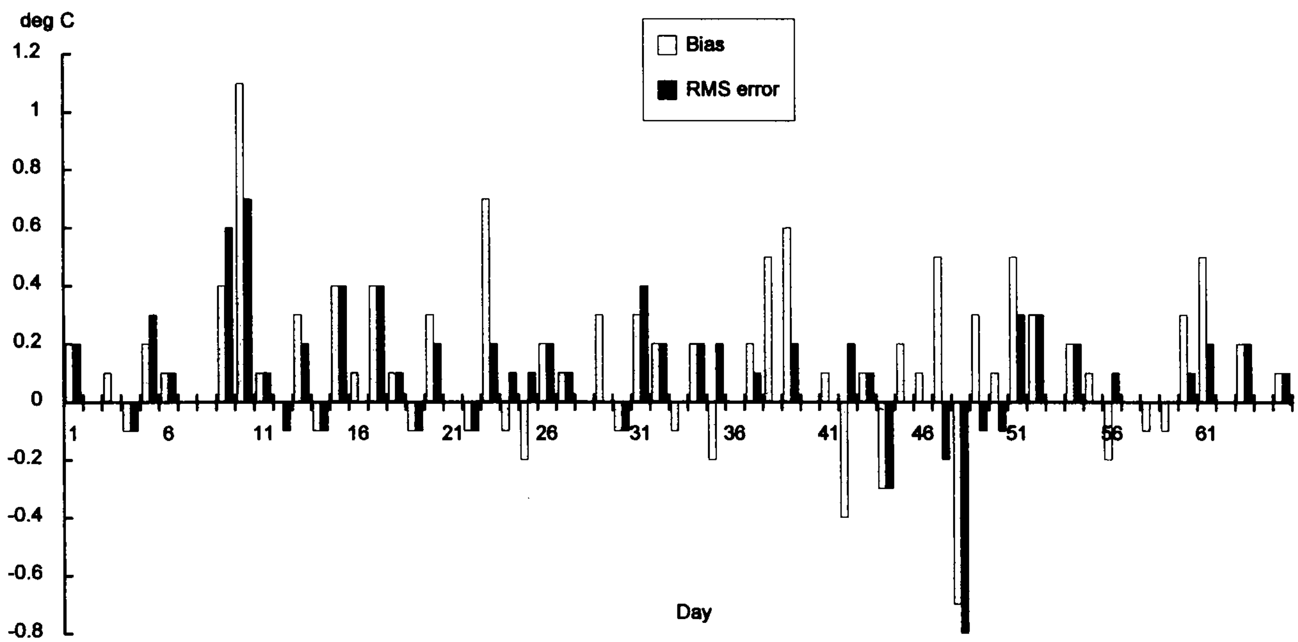

FIGURE 1 Comparison of real-time forecasts with and without midnight adjustment (Chapman's Hill, January 12, 1988, to December 3, 1989).

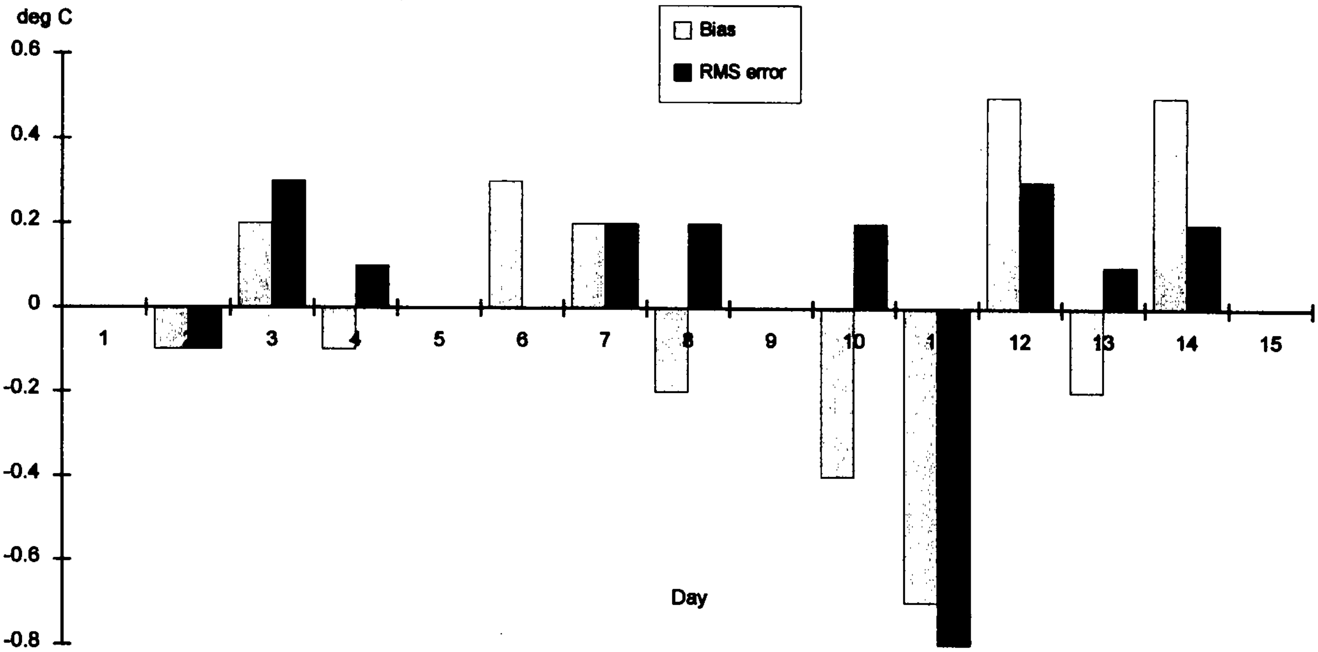

FIGURE 2 Comparison of real-time forecasts with and without midnight adjustment (Chapman's Hill, marginal nights).

in Table 5. The scale of correction depends on the magnitude of the latest actual tendency of air temperature, the calculated intensity of solar radiation, and the value of the forecast itself.

The results of nowcasts of air temperature with and without this self-learning scheme are listed in Table 6. Generally, there is a small reduction in RMS error, accompanied by a small increase in bias, for 2-, 4-, and 6-hr nowcasts by the scheme. The results of site SM001 appear more positive than those of site NO001, especially for overall temperature nowcasts. It is noticed in the study that in some circumstances the method can be very helpful. Figure 3 shows an example of 4-hr nowcasts of air temperature at site SM001 with and without self-learning and correction. The figure indicates that the method enables the model nowcasts to closely track variation in actual temperature, especially after sunset and sunrise.

Discussion

In this study, two simple methods are explored to improve 24-hr forecasts and 2- to 6-hr nowcasts of road surface temperature in real-time application through deduction of midnight error of model prediction from the after-midnight predictions and through trend correction of air temperature, respectively. A comparison of 24-hr forecasts with and without midnight adjustment shows that the method is effective in most cases, with a

TABLE 5 Rules for Correction of Air Temperature Forecasts in Nowcasting

Rule 1:	IF(forecast trend is not consistent with the latest actual trend), and
	IF(it is day time), and
	IF(relative humidity < 90%), and
	IF(forecast declines) -------> Positive correction.

Rule 2:	IF(forecast trend is not consistent with the latest actual trend), and
	IF(it is night time), and
	IF(relative humidity < 90%), and
	IF(forecast climbs) -------> Negative correction.

Default:	Zero correction.

TABLE 6 Comparison of Nowcasts With and Without Self-Error-Correction

	NO001				SM001			
	Overall		Minimum		Overall		Minimum	
	Bias	RMS	Bias	RMS	Bias	RMS	Bias	RMS
2 hour:								
Corrected	0.08	0.96	-0.06	0.31	0.17	1.02	0.04	0.33
Not corrected	0.04	0.99	-0.04	0.32	0.09	1.12	0.01	0.36
Improvement	-0.04	0.03	-0.02	0.01	-0.08	0.10	-0.03	0.03
4 hour:								
Corrected	0.14	1.31	-0.14	0.64	0.28	1.54	0.18	0.74
Not corrected	0.12	1.31	-0.07	0.64	0.26	1.68	0.33	0.78
Improvement	-0.02	0.0	-0.07	0.0	-0.02	0.14	0.15	0.04
6 hour:								
Corrected	0.07	1.86	-0.19	0.82	0.49	2.03	-0.10	0.95
Not corrected	0.06	1.94	-0.06	0.82	0.31	2.20	0.16	0.96
Improvement	-0.01	0.08	-0.13	0.0	-0.18	0.17	0.06	0.10

general reduction of bias and RMS error of about 0.1°C to 0.2°C. The method is an especially useful tool for improving minimum temperature forecasts. The trend correction method, however, does not significantly and consistently improve nowcasts, although it has demonstrated its effectiveness in some cases. It could be useful at some sites but may be useless at others. Generally, both methods show positive results in this study.

The main drawback of the methods, as shown in the paper, is that there is no general rule to predict when they will succeed or fail. This is particularly true when weather conditions on one day are largely different from those of the previous day. To overcome this drawback, detailed historical information about tendency and variation of the error in forecast input is required. More sophisticated methods (e.g., neural network analysis) are needed to analyze and recognize error patterns. This will improve the accuracy of road ice prediction but will also inevitably require a large quantity of computing power and space. To achieve a more fundamental and consistent improvement, further study is needed.

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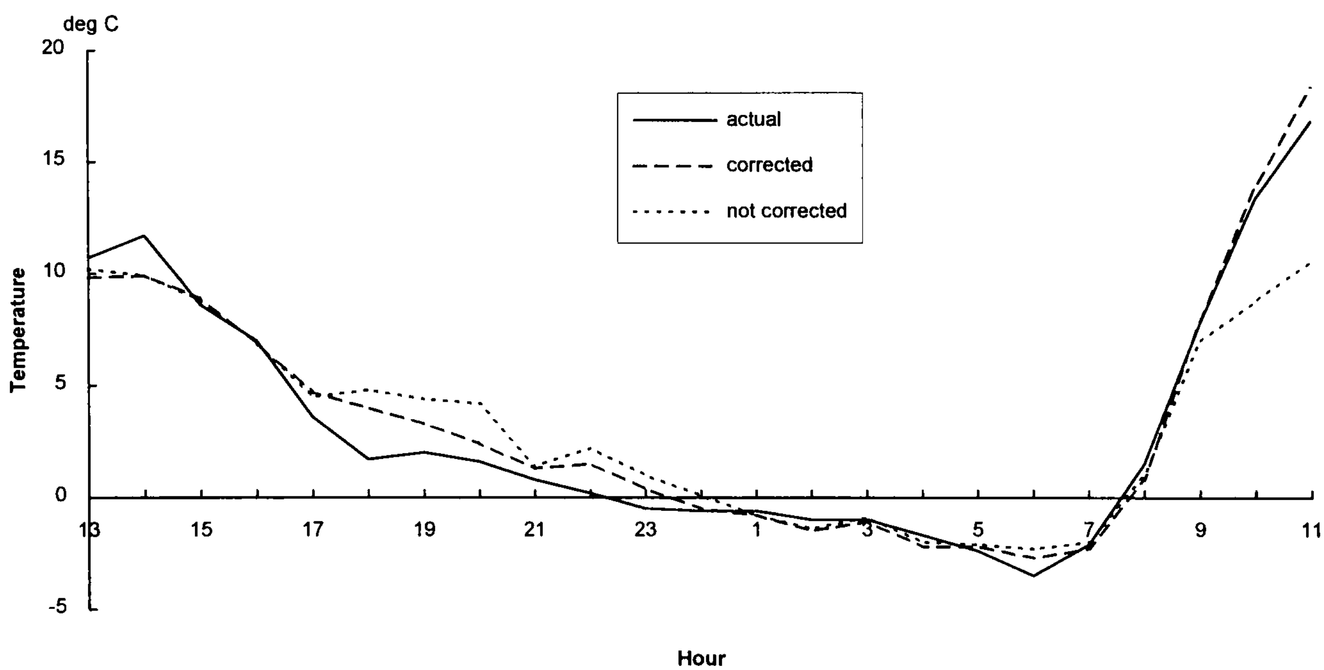

FIGURE 3 Comparison of 3-hour nowcasts with and without correction of air temperature forecast (SM001, January 26, 1994).

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