Software System for Road Condition Forecast Correction

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ARTICLE HISTORY
Compiled March 24, 2020

ABSTRACT
In this paper, we present a monitoring system that allows increasing road safety by predicting ice formation. The system consists of a network of road weather stations and intelligence data processing program module. The results were achieved by combining physical models for forecasting road conditions based on measurements from stations and machine learning models for detecting incorrect data and forecast correction.

KEYWORDS
Anomaly detection, road weather information systems, machine learning, gradient boosting

1. Introduction

Road safety is a complex issue that includes many aspects. Some of them depend on human behavior; others depend on infrastructure conditions. For example, in many regions of the Russian Federation, spring and autumn temperatures can fluctuate near 0\textdegree C, which in combination with rains and high humidity could lead to ice formation on the roads. Detection of these conditions is essential for road safety.

Online monitoring allows preventing road accidents by early maintenance; for example, we can use video monitoring of roads' conditions. Machine learning techniques enable detecting ice formation automatically. For instance, in Zhao, Wu, and Chen (2017), the authors used data collected from stationary cameras to distinguish between five different conditions of the road pavement. In Roychowdhury, Zhao, Wallin, Ohlsson, and Jonasson (2018), authors proposed to collect video from vehicle front cameras instead of static cameras, and to use a more accurate classification technique based on convolutional neural networks.

Despite all their advantages, video monitoring with ordinary cameras struggles with black ice detection. In order to fix this problem we can use multispectral cameras Gregoris, Yu, and Teti (2004), NIR cameras Jonsson, Casselgren, and Thörnberg (2014), or measure depth with Kinect sensor Abdalla, Iqbal, and Shehata (2017). These techniques are more expensive than ordinary cameras; however, they can provide better results.

A video monitoring system is costly. It can be reasonable to use sensors that collect other characteristics of road conditions like temperature, humidity, pressure, and
others. Stations collecting this sort of data are called road weather information systems (RWIS). They can be located on the sides of roads or even inside the pavement [Tabatabai and Aljuboori (2017)].

By processing historical information on road conditions, we can predict ice formation. We can group forecasting algorithms into two major categories. The first category uses physical models [Barber (1957); Dai, Zeng, Dickinson, Baker, Bonan, Bosilovich, Denning, Dirmeyer, Houser, Niu, et al. (2003); Feng and Feng (2012); Sass (1997) or their combinations like in Chunlei and Changyou (2009)]. The authors combine results of the physical models Common Land Model (CoLM) and BJ-RUC FAN, CHEN, ZHONG, and ZHENG (2009), which allowed increasing the accuracy. Later in this paper, we take a closer look at the physical model METRo. It performs exceptionally well in countries like Czech Republic Sokol, Zacharov, Sedlák, Hošek, Bližnák, Chládová, Pešice, and Skuthan (2014), Canada Crevier and Delage (2001), USA Rutz and Gibson (2013), China FAN et al. (2009).

Despite impressive track records, physical models have several problems. The main disadvantage is their computational complexity since they require the numerical solution of partial derivative equations. Another challenge is the deterministic nature of their forecasts. These algorithms provide forecast values but struggle with delivering a level of confidence. It is possible to solve this issue with the Mont-Carlo simulation Berrocal, Raftery, Gneiting, and Steed (2010); Chapman (2012), but it significantly increases computational complexity. Another challenge for this kind of models is anthropogenic factors, which are extremely difficult to estimate. There are some approaches with an additional prior assumption about anthropogenic factor behaviour Khalifa, Marchetti, Bouilloud, Martin, Bues, and Chancibault (2016), but still, they cannot deal with stochastic effects and increase already significant computational complexity.

Another big group of techniques uses machine learning and statistical approaches to road conditions forecast. Even a simple linear regression allows to get reasonable forecasting accuracy; however, usually, people use these methods as part of more complex solutions Diefenderfer, Al-Qadi, Reubush, and Freeman (2003); Liao, Chen, Chen, and Huang (2009); YANG, PENG, and LIU (2010). Using more sophisticated machine learning algorithms like deep neural networks allows getting even better forecast accuracy Gensler, Henze, Sick, and Raabe (2016); Zaytar and El Amrani (2016). However, this family of methods is not a silver bullet and has its problems. For example, a lack of physical assumptions in modeling leads to a lack of interpretability and a constant need for additional refitting to work in a new environment.

It seems that both physical and machine-learning-based techniques have their problems; this is why we decide to build a hybrid system that would combine advantages of both types of models. Another challenge is the quality of the data in such big systems of sensors; it is pretty standard that some devices become malfunctioning, and it is crucial to detect these broken sensors as soon as possible.

In this paper, we describe algorithmic techniques and software system, which allows achieving the stated goal. To build an intelligence system for analyzing RWIS data, we create a software system that takes the data from the sensors, validate if this data correct. For the validated data, a forecasting model provides forecast of road conditions, and these predictions are used to decide on further maintenance actions. We concentrate on the correction of weather forecasting using machine learning and anomaly (outlier) detection. Also, we briefly describe the implementation of the software system.

In section 2 we discuss an approach for weather forecasting. We propose an algorithm that combines classical energy balance based model and correction of residuals
with Gradient Boosting on Decision Trees. In the section 3, we present an approach for
detecting broken RWIS sensors. In section 4, we demonstrate achieved performance
on real-world data collected from RWIS. And finally, in section 5, we discuss some
technical details about software system implementation.

2. Road Weather Condition Forecasting

In this section, we present a new approach for road weather condition forecasting
based on a combination of an energy balance model and machine learning. Both of
them have their pros and cons. So a combination of these techniques allows increasing
the accuracy of forecasting.

2.1. METRo

We choose METRo (Model of the Environment and Temperature of Road) as a primary
weather forecasting model [Crevier and Delage 2001]. This approach already demon-
strated great performance in various cases around the globe. Initially, this model was
tested on Canadian roads; climate similarity between Canada and Russia makes this
model a good candidate for the final approach.

The core idea behind the model is to decompose temperature weave in several parts

\[ R = (1 - \alpha)S + \varepsilon I - \varepsilon \sigma T^4_a - H - L_a E \pm L_f P + A, \]

here \((1 - \alpha)S\) is an absorbed incoming radiation flux, \(\varepsilon I\) is the absorbed incoming
infrared radiation flux, \(\sigma T^4_a\) is an emitted flux, \(H\) is a turbulence flux, \(L_a E\) is the
latent heat flux, \(L_f P\) is a water phase changing flux, finally \(A\) is an anthropogenetic
flux.

We skip the detailed explanation of calculating these parts and coefficients selection,
see the original paper for details [Crevier and Delage 2001]. For us, the anthropogenic
part is the most interesting. A partial derivative equation cannot model this component
because it is highly non-deterministic and so it introduces additional forecasting error.
However, we can fix the error produced by this factor by using a machine learning
algorithm.

2.2. Forecast improvement with gradient boosting

To correct the METRo forecast, we predict the difference between its result and the
real values of road parameters. Here we illustrate this approach using four parameters
predicted by the METRo model: air, road, and under road temperatures and humidity.

Let \(y_t\) be one of the target variables at time \(t\), \(y^M\) be the value predicted by the
METRo model. We build an approximation of the difference between the real value
and predictions \(\Delta y_t = y_t - y^M_t\).

We construct an approximation function \(\Delta y_t \approx F(x_t)\), where \(x_t\) is a feature vector
that represents road condition at time \(t\). These features can be grouped into three
classes:

(1) Historical features collected from Road Weather Information Systems. They in-
clude information about air, road, and underground temperatures, etc.
(2) Information about year season and time of the day. Since these features have a cyclic nature, we encode them by using trigonometric functions. Number of days since the beginning of the year $d$ produces two values $\sin(d/365)$ and $\cos(d/365)$ or $\sin(d/366)$ and $\cos(d/366)$ in case of a leap year. Hour of the day $h$ is transformed into pair $\sin(h/24)$ and $\cos(h/24)$.

(3) Previous predictions from METRo equations.

We build an approximation function $F(x)$ by minimizing a specified loss function $L(\cdot, \cdot)$, which characterizes forecast accuracy:

$$
\hat{F} = \arg \min_F \sum_{t=1}^{T} L(F(x_t), \Delta y_t).
$$

To find this optimal $\hat{F}$, we use the Gradient Boosting algorithm [Friedman (2002)]. Its main idea is to build a sequence of regression models, a combination of which provides a good approximation. At step $N$, the approximation has the form:

$$
\hat{F}_N(x) = \sum_{i=1}^{N} \alpha_i h_i(x),
$$

where $h_i$ is a regression model with weight $\alpha_i$. On step $N+1$ we solve the optimization subproblem to get the model $h_{N+1}$:

$$
Q_{N+1} = \sum_{t=1}^{T} L(\hat{F}_N(x_t) + \alpha_{N+1} h_{N+1}(x_t), \Delta y_t) \to \min_{\alpha_{N+1}, h_{N+1}}.
$$

To get $h_{N+1}$ we solve the subproblem:

$$
h_{N+1} = \arg \min_h \sum_{t=1}^{T} ((-\nabla Q_{N+1}^t) - h(x_t))^2, \quad [\nabla Q_{N+1}^t]_{t=1}^{T} = \left[ \frac{\partial L(z, \Delta y_t)}{\partial z} \bigg|_{z=\hat{F}_N(x_t)} \right]_{t=1}^{T}.
$$

To find optimal $\alpha_{N+1}$ value, we solve the following optimization problem by the linear search:

$$
\alpha_{N+1} = \arg \min_{\alpha} \sum_{t=1}^{T} L(\hat{F}_N(x_t) + \alpha h_{N+1}(x_t), \Delta y_t).
$$

As a loss function we use the Mean Absolute Error:

$$
MAE = \frac{1}{T} \sum_{t=1}^{T} |\Delta y_t - \hat{F}(x_t)|.
$$

For constructed $\hat{F}(x)$ the final prediction is:

$$
\hat{y}_t = y_t^{\text{METRo}} + \hat{F}(x_t).
$$
We construct 12 different regression models to predict air, road, underground temperatures, and humidity for the forecast horizons of 1, 2, and 3 hours.

3. Broken Sensors Detection

Accuracy of road condition forecasting depends on the quality of the data. It is crucial to detect malfunction sensors as soon as possible. Wrong data could lead either to conducting maintenance actions for no reason or, even worse, to miss the dangerous road conditions.

Malfunctioning sensors generate abnormal data, and so we can detect broken sensors by detecting anomalies in data. By anomaly, we consider the observation that deviates from others so much that we could suspend that it came from another source [Hawkins (1980)]. To find these values, we build an anomaly detector, i.e., the function such that:

\[ f(y_t) = \begin{cases} 
  1 & \text{if } y_t \text{ is normal}, \\
  -1 & \text{if } y_t \text{ is anomaly}. 
\end{cases} \]

To construct the anomaly detector we

1. predict a future value \( \hat{y}_t \) of the target variable,
2. compare it with the actual value \( y_t \) of the target variable.

If the difference \( \Delta_t = |y_t - \hat{y}_t| \) is big, this could mean that something drastically has changed, and this could be a symptom of a broken sensor. The anomaly detection function takes the form

\[ f(y_t) = \begin{cases} 
  1 & \text{if } \Delta_t \leq \Delta, \\
  -1 & \text{if } \Delta_t > \Delta. 
\end{cases} \tag{1} \]

Accurate selection of threshold \( \Delta \) is very important: we have to reliably distinguish between cases of just random fluctuations and anomalies due to malfunctioning sensors.

Usually, the value of \( \Delta \) is selected based on a holdout set or using the cross-validation procedure [Friedman, Hastie, and Tibshirani (2001)]. However, for that we need labeled data. Since broken sensors are not frequent events, even such a significant amount of data like we have does not contain enough examples of anomalies. Moreover, labeling is a tedious task. Therefore, we propose to use artificially generated anomalies to select the threshold. We group all anomalies into three different categories:

1. Single anomalies, which can result in some deviation. They are modeled with uniform distribution, see Fig. [1]
2. Short-term anomalies modeled as a Poisson noise with random parameters see Fig. [2]
3. Long-term anomalies, which can be results of some significant dis-functioning in sensors or networks. They were modeled with a Gaussian noise, see Fig. [3]

To find threshold \( \Delta \), we select a subset of data, add these artificial anomalies, and find the value of \( \Delta \), which provides the optimal \( F_1 \) score:

\[ F_1 = \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}, \tag{2} \]
where recall is the fraction of correctly identified anomalies, while precision is the fraction of anomalies we are able to find.

4. Results

4.1. Forecasting Correction

This section discusses the experimental results of road condition forecasting based on a combination of the METRo model and gradient boosting residual correction.

We collected data for seven years from 2012 till 2019 from 120 RWIS, located in different regions of Russia. This data was split into two parts. We fit the model based on data for the period 2012 – 2017 years. We also split data based on different RWIS locations. So, in the end, we have the test data from a later period of time, and from RWIS that were not used while building a model. We measured the Mean Average Error between the predicted value and the real one.

We compare our results with and without additional residual corrections. Example of prediction are presented in Fig. 4. Table 1 demonstrates that additional machine learning post-processing allows for increasing the accuracy of the final forecast.

4.2. Anomaly Detection

This section discusses experimental results of predicting broken sensors of RWIS. Let us consider experimental settings, metrics and final accuracy indicators.
We select 59 RWIS stations from various regions of the Russian Federation. We use data from 50 stations for training models and data from 9 stations for testing the quality of the resulting model. The training set was split into two parts. Data from 35 RWIS was used to build a model; data from another 15 RWIS was used to tune threshold value based on artificially generated anomalies.

We labeled data (normal/anomaly) from the 9 test stations manually. Final results were evaluated by using $F_1$ score.

We compare our approach with other anomaly detection techniques like Elliptic Envelope Butler, Davies, and Jhun (1993), Isolation Forrest Liu, Ting, and Zhou (2008), OneClassSVM with Gaussian kernel Schölkopf, Smola, Williamson, and Bartlett (2000). We also test different regression algorithms to construct approximation $\hat{F}(x)$ beside gradient boosting over regression trees, specifically ridge regression Marquardt and Snee (1975) and multi-layer perceptron Murtagh (1991). Results of the comparison are presented in Table 2. We can see that the proposed approach based on gradient boosting outperforms all other algorithms in terms of the $F_1$ score, see formula 2. Table 1 demonstrates that if before making predictions with METRo model we remove anomalous data, we can significantly improve forecasting accuracy. Note that when detecting anomalies we did not use METRo model for estimating $\Delta t$ in formula 1.
Figure 4. Road Temperature Forecasting Example

Table 2. Anomaly Detection Results

| Algorithm   | LOF  | Ell.Env | OCSVM | IForest | Ridge | MLP   | Boosting |
|-------------|------|---------|-------|---------|-------|-------|----------|
| Recall      | 0.513| 0.719   | 0.904 | 0.395   | 0.668 | 0.637 | 0.753    |
| Precision   | 0.502| 0.482   | 0.130 | 0.252   | 0.758 | 0.738 | 0.797    |
| $F_1$-score | 0.507| 0.577   | 0.227 | 0.308   | 0.710 | 0.684 | 0.774    |

5. Implementation

Initially, company MinMax94\(^1\) has already installed a system for road condition forecasting, which consists of the METRo module and decision-making module connected to the MongoDB. We developed a system that could be easily added to this existed infrastructure.

To do this, we developed two web services based on python library Flask and put them into a docker container. They communicate with the outer world by HTTP requests.

The dataflow is presented in Fig. 5. So the whole work process can be described as follows: data from RWIS goes into the database, then the data is sent to the Anomaly Detection Module. The module generates labels (normal/anomaly) for each observation. If there are many anomalies, we don’t use information from these sensors before they would be checked and fixed. Information about which observations are anomalous is saved in the database.

If the data is normal we send it to the METRo module, which builds predictions. The results are sent to the Residuals Correction module. Results of this module are sent back to the database, and finally, they are passed into the decision-making module, which decides if the road needs maintenance or not.

Models for Anomaly Detection and Residuals Corrections are constructed in advance. We collect historical data in CSV format, as described in section 4. Then we use the lightgbm library Ke, Meng, Finley, Wang, Chen, Ma, Ye, and Liu (2017) to build these predictive models. The whole process takes around 30 minutes on a desktop computer with the Intel Core i7 processor and 32Gb RAM.

\(^1\)https://mm94.ru
6. Conclusion

We proposed a novel approach to improve road surface condition forecasting. It allows for combining the advantages of both energy-balanced and machine learning-based models. Numerical results demonstrate that despite the very impressive accuracy of the METRo model, it is still possible to improve accuracy by correcting residuals of predictions. We describe details of the implementation of these algorithms as a part of the software system for road condition forecasting.

References

Younis E Abdalla, MT Iqbal, and M Shehata. Black ice detection system using kinect. In 2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE), pages 1–4. IEEE, 2017.

Edward S Barber. Calculation of maximum pavement temperatures from weather reports. *Highway Research Board Bulletin*, (168), 1957.

Veronica J Berrocal, Adrian E Raftery, Tilmann Gneiting, and Richard C Steed. Probabilistic weather forecasting for winter road maintenance. *Journal of the American Statistical Association*, 105(490):522–537, 2010.

RW Butler, PL Davies, and M Jhun. Asymptotics for the minimum covariance determinant estimator. *The Annals of Statistics*, pages 1385–1400, 1993.

Lee Chapman. Probabilistic road weather forecasting. In *Proceedings of the Standing International Road Weather Conference (SIRWEC12)*, 2012.

Meng Chunlei and Liu Changyou. Summer road temperature disaster forecast of expressway in beijing [j]. *Journal of Institute of Disaster-Prevention Science and Technology*, 3, 2009.

Louis-Philippe Crevier and Yves Delage. Metro: A new model for road-condition forecasting in canada. *Journal of applied meteorology*, 40(11):2026–2037, 2001.

Yongjiu Dai, Xubin Zeng, Robert E Dickinson, Ian Baker, Gordon B Bonan, Michael G Bosilovich, A Scott Denning, Paul A Dirmeyer, Paul R Houser, Guoyue Niu, et al. The common land model. *Bulletin of the American Meteorological Society*, 84(8):1013–1024, 2003.

Brian K Diefenderfer, Imad I Al-Qadi, Stacey D Reubush, and Thomas E Freeman. Development and validation of a model to predict pavement temperature profile. In *TRB 2003 Annual Meeting*, pages 1–21. Citeseer, 2003.

Shui-yong FAN, Min CHEN, Ji-qin ZHONG, and Zuo-fang ZHENH. Performance tests and evaluations of beijing local high-resolution rapid update cycle system [j]. *Torrential Rain and Disasters*, 2, 2009.

Tao Feng and Shide Feng. A numerical model for predicting road surface temperature in the highway. *Procedia Engineering*, 37:137–142, 2012.
Jerome Friedman, Trevor Hastie, and Robert Tibshirani. *The elements of statistical learning*. Springer series in statistics New York, 2001.

Jerome H Friedman. Stochastic gradient boosting. *Computational statistics & data analysis*, 38(4):367–378, 2002.

André Gensler, Janosch Henze, Bernhard Sick, and Nils Raabe. Deep learning for solar power forecasting—an approach using autoencoder and lstm neural networks. In *2016 IEEE international conference on systems, man, and cybernetics (SMC)*, pages 002858–002865. IEEE, 2016.

Dennis Gregoris, Simon Yu, and Frank Teti. Multispectral imaging of ice. In *Canadian Conference on Electrical and Computer Engineering 2004 (IEEE Cat. No. 04CH37513)*, volume 4, pages 2051–2056. IEEE, 2004.

Douglas M Hawkins. *Identification of outliers*, volume 11. Springer, 1980.

Patrik Jonsson, Johan Casselgren, and Benny Thörnberg. Road surface status classification using spectral analysis of nir camera images. *IEEE Sensors Journal*, 15(3):1641–1656, 2014.

Guolin Ke, Qi Meng, Thomas Finley, Taifeng Wang, Wei Chen, Weidong Ma, Qiwei Ye, and Tie-Yan Liu. Lightgbm: A highly efficient gradient boosting decision tree. In *Advances in neural information processing systems*, pages 3146–3154, 2017.

Abderrahmen Khalifa, Mario Marchetti, Ludovic Bouillard, Eric Martin, Michel Bues, and Katia Chancibault. Accounting for anthropic energy flux of traffic in winter urban road surface temperature simulations with the teb model. *Geoscientific Model Development*, 9(2):pp–547, 2016.

Chi-Chou Liao, Bo-Ruei Chen, Shun-Hsing Chen, and Wei-Hsing Huang. Temperature prediction model for flexible pavements in taiwan. In *Performance Modeling and Evaluation of Pavement Systems and Materials: Selected Papers from the 2009 GeoHunan International Conference*, pages 82–89, 2009.

Fei Tony Liu, Kai Ming Ting, and Zhi-Hua Zhou. Isolation forest. In *2008 Eighth IEEE International Conference on Data Mining*, pages 413–422. IEEE, 2008.

Donald W Marquardt and Ronald D Snee. Ridge regression in practice. *The American Statistician*, 29(1):3–20, 1975.

Fionn Murtagh. Multilayer perceptrons for classification and regression. *Neurocomputing*, 2(5-6):183–197, 1991.

Sohini Roychowdhury, Minming Zhao, Andreas Wallin, Niklas Ohlsson, and Mats Jonasson. Machine learning models for road surface and friction estimation using front-camera images. In *2018 International Joint Conference on Neural Networks (IJCNN)*, pages 1–8. IEEE, 2018.

Jonathan J Rutz and Chris V Gibson. Integration of a road surface model into nws operations. *Bulletin of the American Meteorological Society*, 94(10):1495–1500, 2013.

Bent H Sass. A numerical forecasting system for the prediction of slippery roads. *Journal of Applied Meteorology*, 36(6):801–817, 1997.

Bernhard Schönkopf, Alex J Smola, Robert C Williamson, and Peter L Bartlett. New support vector algorithms. *Neural computation*, 12(5):1207–1245, 2000.

Zbyněk Sokol, Petr Zacharov, Pavel Sedláček, Jiří Hošek, Vojtěch Blizňák, Zuzana Chládová, Petr Pešice, and Miroslav Škuth. First experience with the application of the metro model in the czech republic. *Atmospheric research*, 143:1–16, 2014.

Habib Tabatabai and Mohammad Aljuboori. A novel concrete-based sensor for detection of ice and water on roads and bridges. *Sensors*, 17(12):2912, 2017.

Qinghong YANG, Jiuhui PENG, and Yuanyuan LIU. The atmospheric physical quantity and radar echo characteristic of a strong convective weather [j]. *Journal of Arid Meteorology*, 3, 2010.

Mohamed Akram Zaytar and Chaker El Amrani. Sequence to sequence weather forecasting with long short-term memory recurrent neural networks. *International Journal of Computer Applications*, 143(11):7–11, 2016.

Jiandong Zhao, Hongqiang Wu, and Liangliang Chen. Road surface state recognition based on svm optimization and image segmentation processing. *Journal of Advanced Transportation*, 10.
2017, 2017.