Short-time Wind Prediction Model for Train Operation

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1. Introduction

High wind speeds are a major hazard in train operation. Strong crosswinds caused by sea breezes and seasonal monsoons may cause trains to overturn or derail. Due to past accidents involving strong wind, a policy for stopping train operation during high wind became necessary to maintain a high level of safety. This paper seeks to examine a more efficient policy utilizing a wind prediction model.

2. Current Policy

The current policy used by JR East is very straightforward. Anemometers are placed along the rail track at various intervals, and the wind measurements are sent electronically to a control center. If the measured wind speed exceeds a specified safe level, train service surrounding that area is stopped for a period of 30 minutes. This delay is set to ensure that the wind speed has recovered to a safer level.

However, this policy has many faults. There is little proof that a 30 minute waiting period is an adequate recovery period; rather, this delay period is set arbitrarily. This waiting period also often causes unnecessary delays, inconveniencing passengers and halting large areas of service for extended periods of time. This policy is also reactive rather than proactive, in that trains service is stopped after the wind speed already reaches a dangerous level. Therefore, in order to reduce train delay time while improving train safety, a new policy was studied that uses a prediction model to determine when the wind speed reaches a dangerous level.

3. Prediction Model

By using a prediction model, the past wind history is used to predict what may happen in the future. With a prediction model, trends in the wind speed can be detected, thereby stopping train service before the wind reaches a critical level. Train delay times are also reduced because the 30 minute delay time is no longer necessary. Two prediction models were studied- the difference auto-regressive (DAR) model, and trend auto-regressive (TAR) model.

3a. The Difference Auto-Regressive Model

The DAR, or difference auto-regressive model, predicts future wind speeds based on linear combinations of immediate past data history. First, the data is "differenced" to make the time series stationary. Next, 6 orders of AR models from 0 to 5 are calculated as follows:

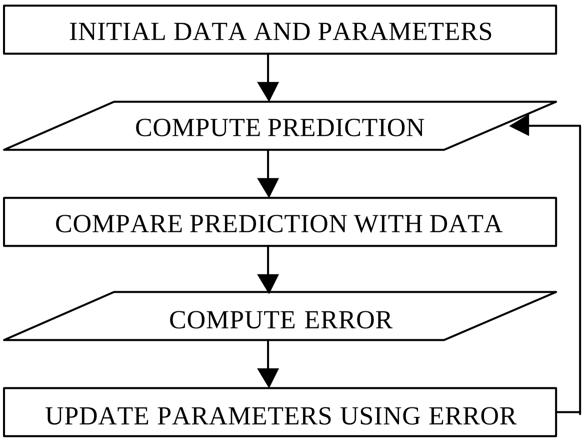
$$y_t = k_1 y_{t-1} + k_2 y_{t-2} + \ldots + k_n y_{t-n}$$

where y is the data point, t is the time step, k is the AR coefficient, and n is the AR order. Calculations beyond the 5th order AR model would increase computation time significantly with only a small benefit. The performance of each AR model is determined using the Akaike Information Criterion (AIC), which is similar to the least-squares method. The optimal AR model is then used to make future predictions through iteration. The 5th order AR model is very often the optimal model, because it has a longer "memory" of the past history. However, because a maximum of 5 data points is used to make a prediction, only very short term trends can be detected with this model.

3b. The Trend Auto-Regressive Model

The TAR, or trend auto-regressive model, is similar to the AR difference model, but includes a trend component. The trend is calculated using the Kalman filter, and the AR component is calculated using the residual stationary data. Kalman filters are widely used today in prediction models, from navigation systems to economic projections. The Kalman filter is also well suited for the wind prediction model. It is able to filter out the chaotic shocks or gusts found in wind speed measurement. It is also very useful for detecting trends in wind speed, because all past data is used to make the next prediction. The Kalman filter is very adaptive, in that it takes the past error into consideration when calculating future predictions. Once the trend component is calculated, it is then subtracted from the actual data, leaving a stationary time series used by the AR model.

After calculating the predictions of both DAR and TAR models, a safety limit based on the accuracy of past predictions is imposed. A higher limit results in higher safety but greater delay, while a lower limit results in fewer delays but less safety.



The Kalman Filter

4. Testing and Results

These two models are tested on many different sample data sets. All contain data taken at 3 minute intervals, for time periods of about 1 day. These data sets represent a large variety of wind patterns, from smooth to chaotic, sporadic to extended gusts, and moderate to strong wind speeds. Future predictions are calculated up to a time span of 36 minutes. Because the maximum travel time between two stations or wind shelter areas for trains is 36 minutes, this time length for forecasting seemed reasonable.

The results of the two models are then compared with the actual data to determine the length of train stopped time. In the case of the two prediction models, train service is suspended when the predictions exceeds the critical wind speed. A penalty is also imposed when the models fail to predict a dangerous wind speed. If the wind speed exceeds the critical level while trains are still operation, the model is penalized. The penalty function carries a much higher penalty to more dangerous wind, such as an excess by 5 m/sec, than marginal excess, such as by 1 m/sec.

When comparing the prediction models with the current rule, the safety limits of the prediction models are set such that the level of safety of the models equals that of the current rule. The ratio percentage of model stopped time to current rule stopped time is then computed. The following table summarizes the results of the comparisons:

	Stopped Time %	
Time	TAR	DAR
~3 min	74	76
3-6 min	72	83
6-9 min	77	92
9-12 min	77	90
12-15 min	81	90
15-18 min	82	88
18-21 min	84	81
21-24 min	87	78
24-27 min	86	77
27-30 min	88	77
30-33 min	93	74
33-36 min	94	72

For predictions of 0 to 18 minutes, the TAR model is superior to both the DAR model and the current rule. Train delay time is reduced by about 20 to 25 percent compared to the current rule, while maintaining an equal level of safety. However, after 18 minutes, the DAR model's performance exceeds the TAR model. The trends calculated in the TAR model become less accurate beyond a certain point. However, even at 36 minutes into the future, the performance of both prediction models exceeds the current rule.

5. Conclusion

So far, the prediction models have shown many advantages over the current rule. While the current rule is arbitrary with no proven methodology, the prediction models can be statistically defined. Train stopped time is also reduced using the prediction models when compared to the current rule. However, the prediction models have some faults as well. The prediction models cannot anticipate sharp changes in wind speed, such as wind gusts. Because of the rather chaotic nature of wind, it will be difficult to account for gusts in the prediction models without reducing delay time. Also, the TAR model performance beyond 18 minutes degrades significantly. Perhaps trends in wind behavior cannot be calculated for more extended periods of time. Fortunately, because a majority of the travel time between stations is under 18 minutes, the TAR model is the most ideal for use.

Reference

Shimamura, M. (1995) New Approach to Strong Wind Prediction and Its Use for Railway Safety Management, Journal of Eastern Asia Society for Transportation Studies, Volume 1, No. 1, pp 1-10