New Approach to Strong Wind Prediction and Its Use for Railroad Safety Management

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abstract: This paper is concerned with appropriate safety rules of train operation at locations prone to wind hazard. This is achieved via the development of reliable and inexpensive procedures for strong wind forecast on the spot. The developed tool for this target is a statistical prediction model for the time series of wind velocity based on the preceding wind observation data. The results of the hypothetical application of this model to the train traffic procedures demonstrates the validity of this model in terms of safety improvement and reduction of shutdown time in the train operation under strong wind.

1. THE PROBLEM

Safe and efficient operation of a railroad system is the most important role of commercial railroads. Under this circumstance, the strong driving winds are one of the major hazards to derailment and overturning of trains in Japan, where monsoon and typhoon are quite rampant and routine natural events. A train was overturned from a tall bridge by seasonal wind in December, 1986 in the western district of Japan, and 6 persons were killed in the accident. Recently, other two similar accidents occurred in the northern district of Japan. Hence, the train safety against strong driving wind has become a highly important issue in Japanese railroad society.

Japanese railroad companies conduct monitoring of the wind velocity and its associated operational regulation to protect trains at the specific places frequently observing the strong driving winds along the railroads (1). Anemometers are located at the top of poles near the railroad track in those places, and the measurements are electrically transferred to the nearest station. Currently, the most of the railroad companies utilize a common type of regulatory criteria on their train operations to avoid wind accidents. The basic idea of the criteria is to introduce some operational margins in the time and wind velocity measures. A threshold value involving a safety margin of the wind velocity is used to decide if the train operation should be stopped. Once when a strong wind exceeding the threshold is observed, the train operation is suspended, and the regulation is continued for a certain marginal time period, e.g., 30 minutes at least to watch the further possibility of the strong wind.

A typical regulatory rule of train operation which is applied to track locations prone to wind hazard such as tall bridges and embankments would be formalized as below.

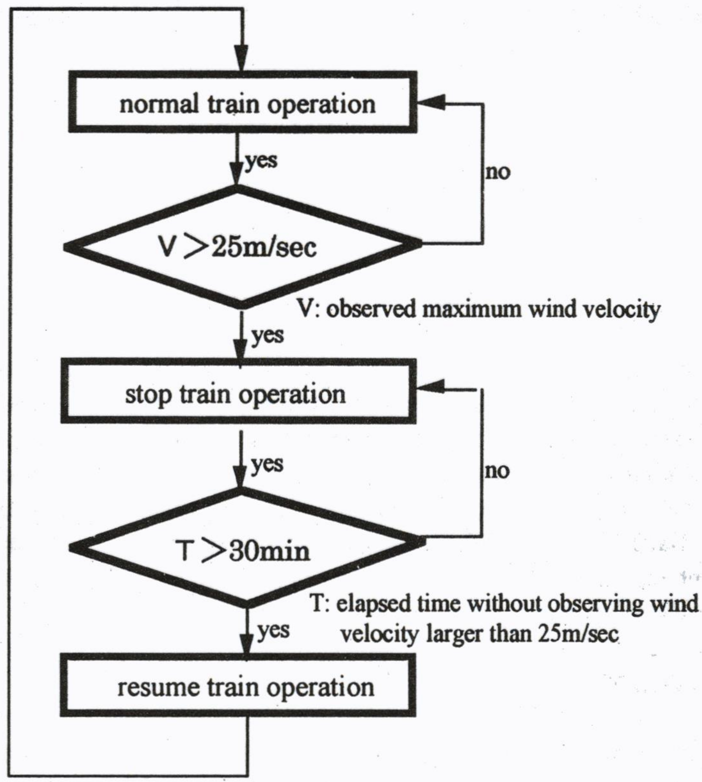

FIGURE 1 A schematic flow of regulatory rule of train operatin in case of strong wind

In the past, the threshold wind velocity to stop train operation was 5 m/sec higher than the current one and the criterion to resume operation was based on use of human expertise. But the fatal accident mentioned above raised questions about the existent regulatory rule which should be the safeguard of train operation against wind threat. An extensive research was carried out about causal relations of the accident. And it was suggested that the velocity of the wind which overturned the victim train would not have been much higher than the threshold wind velocity to stop train in the existent rule and the arbitrary resumption of train operation might have routinely been exposing the trains to the risk of the "sudden attack" of strong wind.

As the result, the railroad companies changed the existent threshold wind velocity to stop train operation toward more conservative direction and amended the resumption rule to be completely objective and workable without use of human expertise. However, the resultant reduction of operational efficiency of the railroad system by these changes has grown so significant that it is not rare the operation of a railroad is suspended for almost a whole day in some cases (1), since the regulation at a specific place easily influences the entire schedule of the operation. The place under the regulation becomes a bottleneck on the overall railroad.

Besides, the risk of the accidents is not removed sufficiently even under these conservative regulations. They can not sufficiently decrease the possibility that the train gets a strong driving wind immediately before and after the regulation period (2).

The main reason of the risk and inefficiency is considered to be the current inflexible and unreasonable regulatory criteria on the train operations. The operational margins in both of the time and wind velocity domains have few objective backgrounds to guarantee the significant reduction of the risk and the maintenance of the efficiency, because they are mainly determined by the past experiences of the train operators, and also their fixed values at predetermined levels are not associated with the actual wind changes under an individual weather condition.

An efficient remedy to these difficulties will be to introduce the predictive information of a few minutes later on the wind velocity at the monitoring place. If the prediction is quite reliable and accurate, this idea enables the credible and flexible regulation on the train operation around the place of the bottleneck, and the risk of the strong wind and the entire efficiency of the railroad operation will be significantly improved. The most straightforward approach for the wind prediction might be the method to perform the predictive simulation based on a meteorological atmosphere model (1-5). However, since various factors such as air pressure distribution and topography around the place influences the wind generation, the meteorological model generally becomes highly complex and inaccurate. Accordingly, this approach may not be very appropriate for the purpose of reliable and real-time wind prediction in the current state of the art.

2. OUTLINE OF RESEARCH

The purpose of the work reported here is to propose a novel approach to predict reliable and accurate wind velocity based on a statistical methodology and to demonstrate its feasibility for the regulation on railroad operation. The approach can derive the future change of the wind velocity in the next few minutes based on the observed data in the past several hours under the real-time situation.

A new approach to predict the future wind velocity has been developed and tested in an off-line numerical experiment. Figure 2 shows the outline of the experiment. First, the analog signal of wind velocity obtained at a wind monitoring place for a long period was converted into digital data under a certain sampling rate, and the data are stored to files in a computer. Second, a large number of cases involving the duration from the start to the end of highly windy weather were selected from those files. The standard time length of each case is around 9 hours. The data in the former half of the duration for each case was used to build a statistical model of the specific wind dynamics of the case. The model is to relate the data in scores of past steps with several future steps. Thus, the future wind velocity is predicted by substituting scores of the past data to the model.

The performance of the model established for each case was tested through the comparison between the actual wind velocity and the model prediction for the latter half of the duration of the case. The accuracy and reliability of the prediction have been evaluated through the numerical experiments for the large number of cases. Furthermore, the new approach was compared with the conventional regulation criteria through numerical simulations on some of the cases.

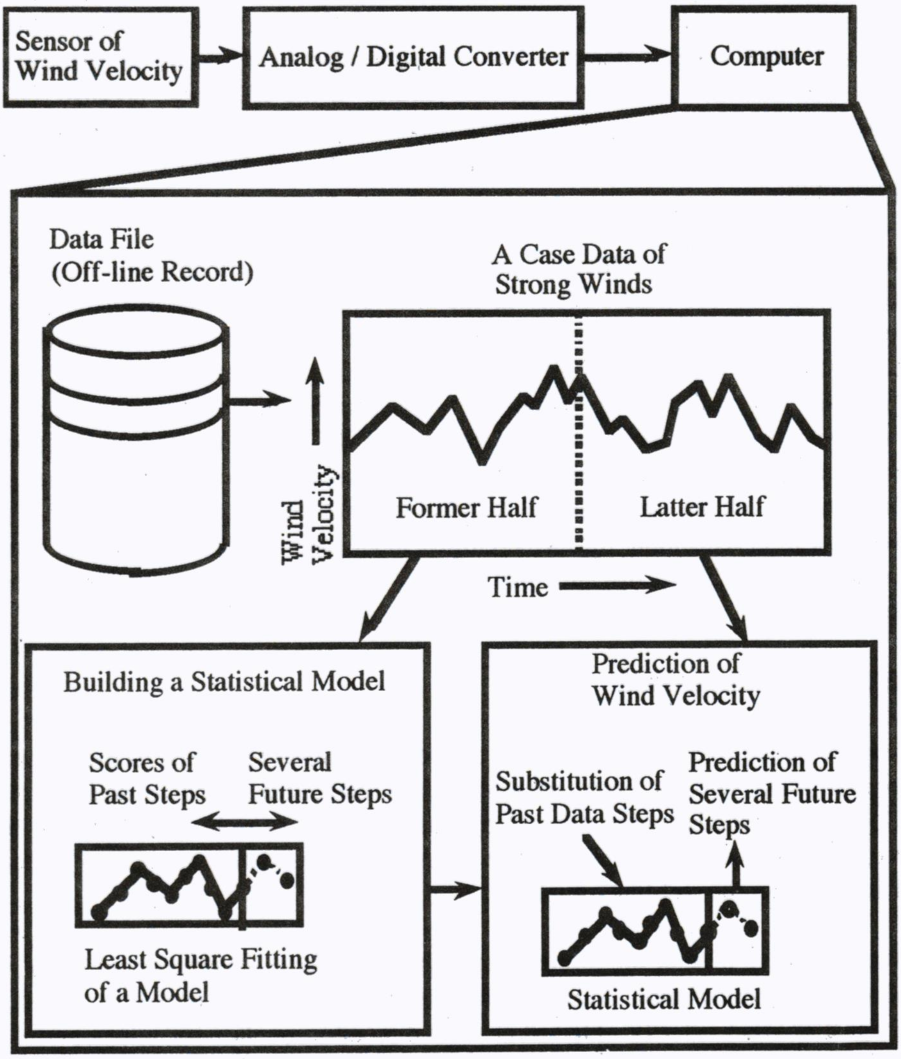

FIGURE 2 Outline of research for wind prediction method.

3. WIND PREDICTION METHOD

The statistical method to predict future wind velocity based on the past observed data consists of several processing steps. Figure 3 shows the block diagram of the processing for the wind prediction.

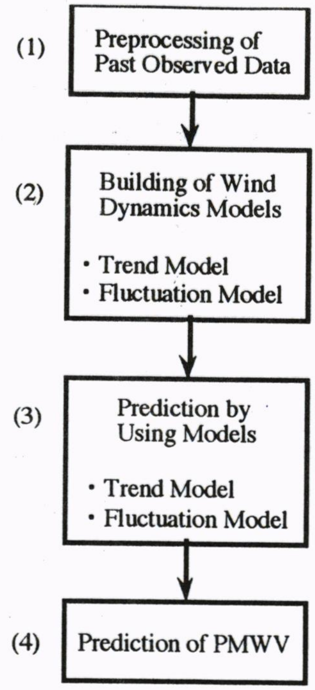

FIGURE 3 Block diagram of wind prediction method

3.1 Preprocessing of Past Observed Data

Since the sampling rate of the raw digital data of the wind velocity is usually the order of several seconds, the data contains wind fluctuation components in very short time scale. These high frequency components behave as if it is noise for more long term prediction such as the order of several minutes. Hence, a filtering operation is applied to the raw data to remove the noisy components for the prediction while maintaining the information in the time scale of a few minutes.

3.2 Building of a Wind Dynamics Model

The changes of the filtered wind velocity can be decomposed into two parts. One is a macroscopic "trend component" over the time scale of several hours. Another is a "fluctuation component" in the time scale of several minutes. These two components have mutually quite different temporal characteristics, since the former is mainly originated by the change of the global air pressure distribution, while the latter depends on the turbulence of the air stream around the objective place. Accordingly, an individual statistical model is built for each component.

For the trend component, the following third order time polynomial model is used to capture the temporal features.

$$x_{tr}(k) = ak^3 + bk^2 + ck + d, \qquad (1)$$

where x_{tr} : trend component, k: time step and a, b, c, d: model coefficients.
The least square fitting of this expression to the former half of the duration of a case, i.e.,

$$e_{tr}^2 = \sum_{k=1}^{n}(x(k) - x_{tr}(k))^2 \rightarrow \text{min}, \qquad (2)$$

where x: filtered actual wind velocity, e: fitting error and
n: number of former half data,
determines all of the model coefficients.

Once if this model is determined, the trend component $x_{tr}(k)$ is subtracted from the filtered actual wind velocity x(k), and the fluctuation component x_{fl} is derived.

$$x_{fl}(k) = x(k) - x_{tr}(k). \qquad (3)$$

Subsequently, this fluctuation component is modeled by using the following auto-regressive expression (4).

$$\hat{x}_{fl}(k) = \sum_{i=1}^{s} a(i) x_{fl}(k-1), \qquad (4)$$

where $\hat{x}_{fl}$: model estimation of a fluctuation component,
a: model coefficients and s: model order.

The model coefficients are determined by the least square fitting similarly to the trend model.

$$e_{fl}^2 = \sum_{k=1}^{n}(x_{fl}(k) - \hat{x}_{fl}(k))^2 \rightarrow \text{min}. \qquad (5)$$

3.3 Prediction by Using a Model

Both of the trend model and the fluctuation model can be extrapolated towards the future time steps. A future trend component $\hat{x}_{tr}$ is easily evaluated by substituting the value of the future time step k to the time polynomial expression (1), while a future fluctuation component $\hat{x}_{fl}$ must be derived through iterative model evaluations as follows.

$$\hat{x}_{fl}(k) = \sum_{i=1}^{s} a(i) x_{fl}(k-i),$$

$$\hat{x}_{fl}(k+1) = a(i)\hat{x}_{fl}(k) + \sum_{i=1}^{s-1} a(i+1) x_{fl}(k-i),$$

$$\bullet \qquad (6)$$

$$\bullet$$

$$\hat{x}_{fl}(k+p) = \sum_{i=1}^{p} a(i)\hat{x}_{fl}(k-i) + \sum_{i=1}^{s-p} a(i+p) x_{fl}(k-i),$$

where p: time step towards future for prediction.

The prediction of the actual wind velocity $\hat{x}$ is obtained by the sum of these two predictions.

$$\hat{x}(k+p) = \hat{x}_{tr}(k+p) + \hat{x}_{fl}(k+p). \qquad (7)$$

3.4 Prediction of Probabilistic Maximum Wind Velocity

The prediction of the wind velocity $\hat{x}$ is just the most likely expectation based on the past observations. The actual wind velocity will easily be larger than this value in probabilistic sense. Accordingly, the upper limit of wind velocity under a certain small probability ε has more practical meaning for the decision making on the operational regulation. The upper limit is named as "Probabilistic Maximum Wind Velocity (PMWV)" in this work, and is evaluated by the following probabilistic test based on the Gaussian error distribution.

$$P(x(k) \geq x^{\varepsilon}_{\max}(k)) = \int_{x^{\varepsilon}_{\max}(k)}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2(k)}} \exp\left(\frac{-(x(k)-\hat{x}(k))^2}{2\sigma^2(k)}\right) dx(x) = \varepsilon \qquad (8)$$

where $\sigma^2 = (e_{tr}^2 + e_{fl}^2)/2$ and $x^{\varepsilon}_{\max}$: PMWV.

By this definition, $x^{\varepsilon}_{\max}$ is always larger than the most likely expectation x(k). The distance between the values of $x^{\varepsilon}_{\max}$ and x(k) is called as the margin of the PMWV.

The steps (1) and (2) are applied to the former half of the data of a case, and the other steps are iteratively conducted for every time step in the later half of the case.

4. PERFORMANCE EVALUATION

The proposed approach has been applied to the wind velocity data sampled at a monitoring place along the railroad line of East Japan Railway Company.

4.1 Margin and Reliability

The accuracy and reliability of the prediction have been evaluated for the large number of cases in which the maximum wind velocities were more than 20m/sec. Table 1 shows the relations between the margin of PMWV and the reliability γ=(1-ε) under the prediction of 3 minutes ahead. If the margin of the PMWV is set to be around 5m/sec, this approach achieves the reliability of more than 99%, i.e., the probability that the actual wind velocity exceeds the PMWV is less than 1%. If the PMWV is used for the regulatory judgment, the performance of the regulation is expected to been enhanced, because the PMWV always suggests a minimum margin while maintaining a negligibly small risk.

The evaluations of the margin and reliability of this approach for the different prediction time lengths and the data of the other wind velocity ranges have also been performed. The results of the evaluation for these conditions were quite similar with the above descriptions.

TABLE 1 Margin and Reliability of Prediction-based Approach

Margin (m/sec)	Reliability (%)
0	50.0
1	83.7
2	92.2
3	96.8
4	98.4
5	99.3
6	99.8
7	99.9
8	100.0

4.2 Comparison with Conventional Regulation

This approach was compared with the conventional regulation criteria through numerical simulations on some cases. Figure 3 depicts a result of the wind prediction for highly strong winds. The strong winds blew over more than 7 hours in this case, and the maximum wind velocity recorded was 27 m/sec. The solid line stands for the actually observed wind velocity, while the dashed line is the most likely expectations of every 3 minutes before. These two lines seem to be very close at each time point, and the standard deviation σ of the prediction error was only 2.8m/sec. The upper short horizontal lines represent the PMWV for every 3 minutes. The reliability γ=(1-ε) was set to be 99.74%, and thus the prediction failure is almost negligible. It is obvious that the PMWVs always specify the upper bound of the actual wind velocity very precisely.

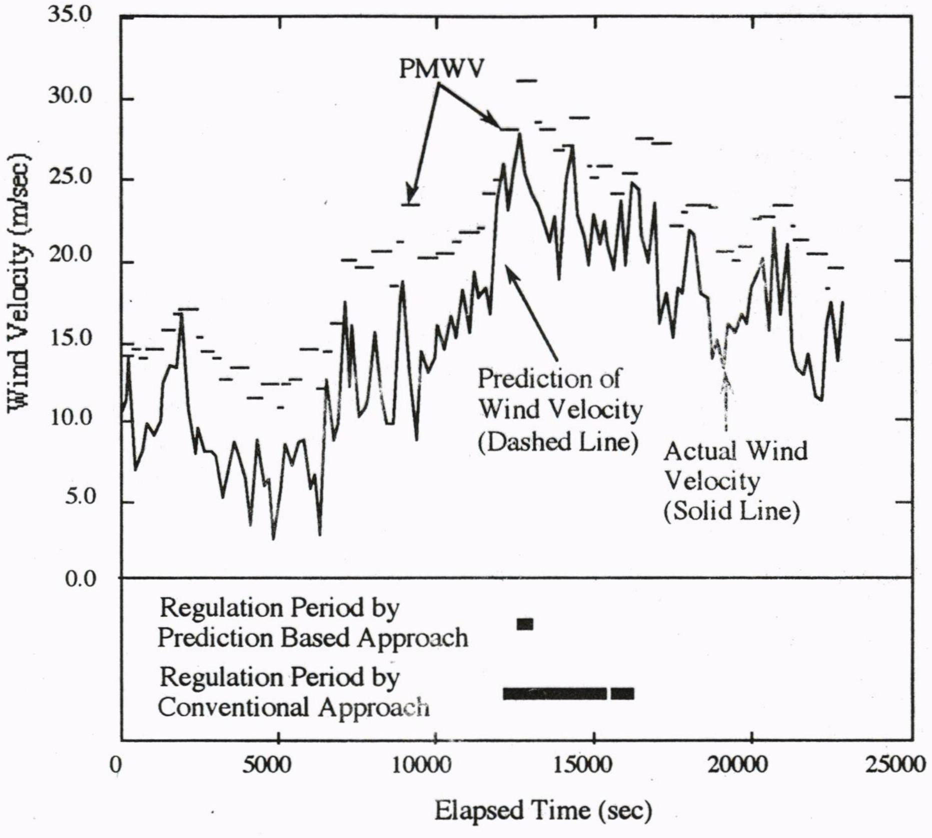

FIGURE 4 An example of the performance of prediction-based approach for observed data

The thick bars at the bottom of the figure indicate the regulation periods suggested by the conventional criteria and our new approach. Generally speaking, the driving wind more than 30m/sec. is considered to be dangerous for train operation. The conventional criteria utilize the threshold value of 25m/sec. to maintain the margin of 5m/sec. which is quite common. Once if the observed wind velocity exceeds 25m/sec, then the train operation is suspended for 30 minutes at least.

On the other hand, in the prediction-based approach, the threshold value of 30m/sec. having no margin is used for the PMWV, because the PMWV already involves its probabilistic margin. Thus, if the PMWV becomes more than 30m/sec. in a certain duration of 3 minutes, the train operation is halted for the 3 minutes only. The length of the regulation period for the conventional criteria was 5040 sec. In contrast, that of the prediction-based approach was only 540 sec. which is nearly one tenth of the conventional one. Furthermore, any risky instants that a train can get the strong wind more than 30m/sec were not allowed in this new approach, while the time point immediately before the regulation starts was a risky instant in case of the conventional method. The performance evaluated for the other cases were almost similar with this result.

5. CONCLUSIONS

A novel approach to predict reliable and accurate wind velocity based on a statistical methodology has been proposed in this work. This approaches was applied to a large number of the actual data of wind velocity in the off-line manner, and its superior performance for the operational regulation of railroad systems has been demonstrated comparing with the conventional regulation method.

A significant advantage of our approach is its objective and reasonable backgrounds to determine the regulatory margin for the wind velocity. Another valuable advantage is its efficiency of the regulation due to the essential feature of the prediction-based approach. The future works remained in our study are (1) to conduct more precise performance evaluation of this approach, (2) to establish new appropriate regulation criteria using the predictive information and (3) to develop an on-line prediction system for the regulation in real use.

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