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Comparison of strong wind forecasts by fluid analysis-based and AI-based methods

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Abstract. Two approaches to forecasting strong winds in railway operations management were evaluated：a fluid analysis-based method and an AI-based method. The fluid analysis-based method estimates wind speed distributions using computational fluid dynamics (CFD) analysis and forecasts the maximum instantaneous wind speed based on the forecasted average wind speed at LFM grid points. On the other hand, the AI-based method uses deep neural networks to learn the relationship between forecasted wind speed and measured maximum instantaneous wind speed at LFM grid points to forecast the maximum instantaneous wind speed. Experimental results using observational wind data from railway lines confirm that the AI-based method can reduce the forecast error by 30-40% compared to the fluid analysis-based method, indicating that the AI-based method is more suitable when observational wind data is available.

Keywords: Large Eddy Simulation, Computational Fluid Dynamics, Deep Neural Network, Deep Learning, Wind Forecasts, Railway, Disaster Prevention

1. Introduction

Measures to reduce the risk of natural disasters are important issues in the management of railway operations in Japan, and as part of these measures, operation controls are implemented in the event of strong winds based on actual instantaneous wind speed values observed by anemometers installed along the railway line. In addition, planned suspension of operations during strong winds is carried out with reference to wind speed forecast values provided by Meteorological Agencies. For example, the Local Forecast Model (LFM) by the Japan Meteorological Agency (JMA), which forecasts wind speeds with a horizontal grid spacing of 2 km, is used. However, for decisions on suspension and resumption of operation, a pinpoint spatial resolution is required, and the spatial resolution of the LFM is not sufficient.

Therefore, we considered two approaches to obtain local wind speed forecasts. The first approach is a fluid analysis-based forecasting method. This method uses CFD analysis with the LES model to obtain the wind speed distribution in the area including the forecast target point and the average wind speed ratio calculated from the LFM grid point and the forecast target point. The average wind speed forecast for the LFM grid point is multiplied by the average wind speed ratio and the gust rate to calculate the maximum instantaneous wind speed forecast for the forecast target point. The second method is an AI-based forecasting approach. This method calculates the maximum instantaneous wind speed forecast value for the forecast target point by learning and forecasting using a deep neural network. It uses the average wind speed forecast value for the LFM grid point as the explanatory variable and the actually observed maximum instantaneous wind speed value for the forecast target point as the objective variable. This paper presents the results of a quantitative comparison with experiments using real data for these two approaches to local wind speed forecasts.

2. Strong Wind Forecasting System for Railway Operations

In this chapter, we introduce the strong wind forecasting system we are developing for railway operations [1]. Figure 1 shows the dashboard screen of the system. The system uses three components to display

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forecasts corresponding to the maximum instantaneous wind speeds from 10 minutes to 24 hours ahead at the locations of anemometers installed along the railway line. The system enables operation managers and maintenance personnel to obtain the necessary information according to their specific work scenarios.

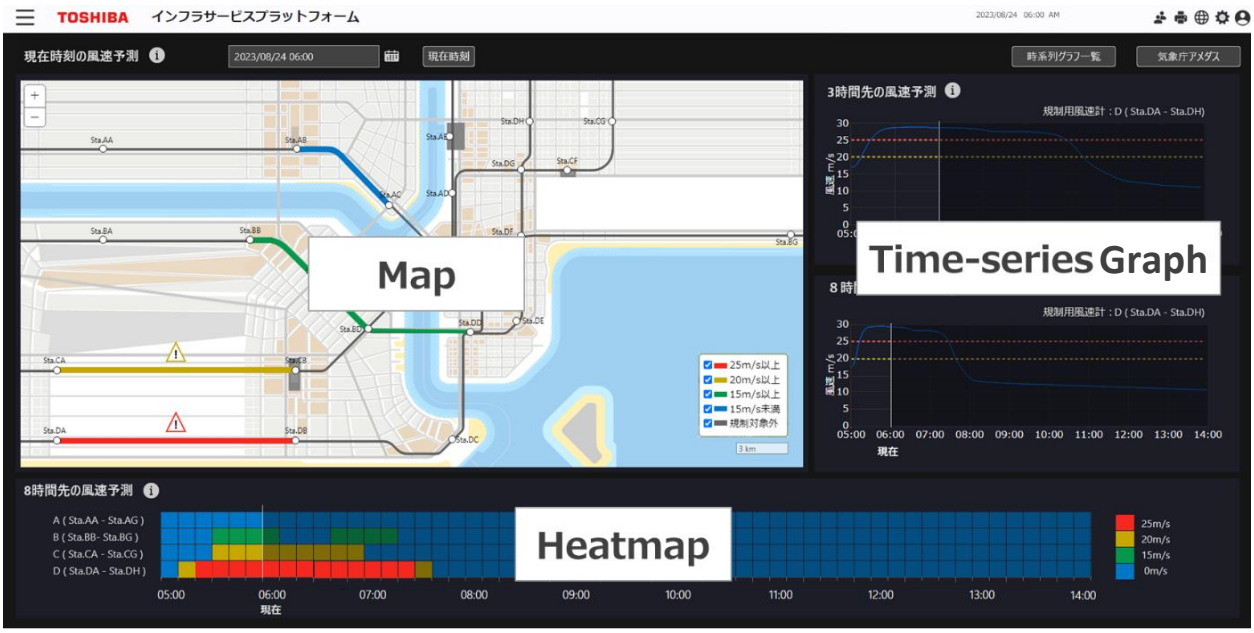

Figure 1 Dashboard screen of Strong Wind Forecasting System for Railway Operations

The map component displays the forecasted wind speed 10 minutes ahead among the forecasted wind speeds at anemometers locations on a railway line map. In addition, the map component has a function that switches colors and icons (red for operation suspension, yellow for speed limit) in accordance with the forecasted wind speeds in the operation control section. This allows users to visually grasp the location and geographical characteristics of the operation control section. The heat map component displays wind speed estimates for up to 24 hours ahead at the anemometer locations. By default, the anemometer name and forecasted wind speeds for operation control section are displayed at 10-minute intervals from one hour ahead to eight hours ahead. However, it is possible to display forecasted wind speeds from one hour ahead to 24 hours ahead at 30-minute intervals by switching a button. This allows users to determine when to issue operation control several hours in advance and when to resume operation after the operation control have been issued. The time-series graph component displays forecasted wind speeds at an anemometer location for the past one to three or eight hours on a time-series graph to help users understand when wind speeds will increase and converge. The system has a function that allows users to switch the display to the time-series graph of the target anemometer by clicking on the icon of the anemometer position in the map component or the cell in the heat map. Furthermore, since the forecasted wind speed values at anemometer locations are stored in a time series database, it is possible to display and check the forecasted wind speed values for past high wind events in various components.

This system is built on Toshiba's industrial IoT (Internet of Things) service, TOSHIBA SPINEX, which ensures high reliability and security. It can be provided as a service that can be accessed using a web browser. Furthermore, TOSHIBA SPINEX provides various components and functions for linking with external services. Therefore, TOSHIBA SPINEX has functions to visualise real-time wind speed measurements with various components and to display information in an event list or send email notifications when wind speeds

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exceed the regulation values, enabling the provision of services to support railway operations in strong winds according to business scenes and regional characteristics.

3. Maximum Instantaneous Wind Speed Forecasting Method

Two approaches to forecasting maximum instantaneous wind speeds in strong wind forecasting systems described in the previous chapter were examined a forecasting method using fluid analysis and an AI-based forecasting method. This chapter provides an overview of both forecasting methods.

3.1. Fluid Analysis-based Method

The fluid analysis-based method uses Computational Fluid Dynamics (CFD) analysis [2]. Figure 2 shows an example of wind resource analysis results. The results for a uniform inflow of 10 m/s wind from the north, including the effects of surrounding topography and buildings, enable the evaluation of the wind intensity distribution in the target area with a spatial resolution of 20 m. The blue points indicate the wind speed distribution in the target area, while the blue dots represent the grid points of the Local Forecast Model (LFM) Grid Point Value (GPV). The LFM, provided by the Japan Meteorological Agency (JMA), forecasts weather elements such as pressure, wind direction, wind speed, temperature, relative humidity, precipitation, cloud cover, and solar radiation at 30-minute intervals up to 10 hours ahead with a high resolution of 2 km horizontal interval for the entire Japan. The red point indicates the evaluation points for the forecast of maximum instantaneous wind speed.

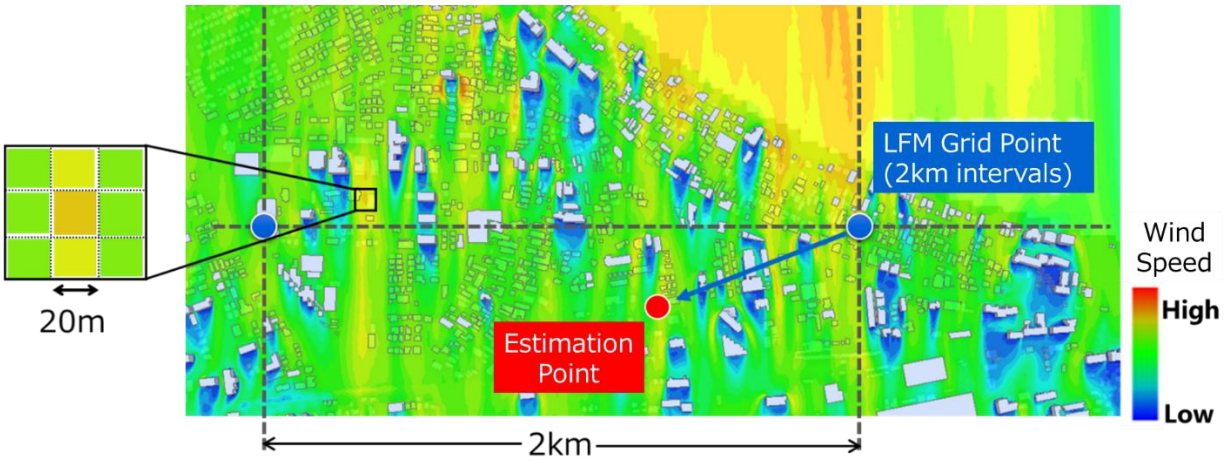

Figure 2 Example of wind resource analysis results

The process flow of forecasting maximum instantaneous wind speed is described as follows. In advance, the wind speed distribution in the target area is obtained by executing the wind condition analysis described above. Then, the average wind speed ratio R_R, which is the ratio of the average wind speed at the evaluation point to the average wind speed at the LFM grid points, and the gust factor GF_R, which is the ratio of the maximum instantaneous wind speed at the anemometer nearest the evaluation point to the average wind speed, are calculated. As shown in Equation (1), the forecasted maximum instantaneous wind speed, $Umax_{est}$, is calculated by multiplying these coefficients to the average wind speed $Uave_{LFM}$ at the LFM grid point.

$$Umax_{est} = Uave_{LFM}(Dave_{LFM}) \times R_R(Dave_{LFM}) \times GF_R(Dave_{LFM}) \quad (1)$$

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Here, $Dave_{LFM}$ is the wind direction at the LFM grid point. The LFM wind direction is classified into 8 directions, and the corresponding wind resource analysis is also performed for the 8 directions to calculate the average wind speed ratio and gust factor. Since the LFM at a given time is a set of wind speed and wind direction, the average wind speed ratio and wind speed increase rate are selected from the wind direction of the LFMM. Since the wind direction of the LFM changes from time to time in the time series, the values of the average wind speed ratio and wind speed increase rate are adjusted accordingly.

3.2. AI-based Method

The AI-based method uses a regression model based on MLP (Multi-Layer Perceptron), a type of deep neural network [3]. Figure 2 shows a conceptual diagram of the AI-based wind forecast method. In this method, wind speed and wind direction at the LFM grid points are used as explanatory variables, and the maximum instantaneous wind speed at the evaluation point is used as the objective variable. The explanatory variables are the wind speed and direction at the four LFM grid points around the evaluation point, and the AI-based model allows transformations to be made for the nonlinear relationship between the LFM grid points and the evaluation point, and between the average wind speed and the maximum instantaneous wind speed. Note, however, that this AI-based method requires observed data compared to the fluid analysis-based method described in the previous section.

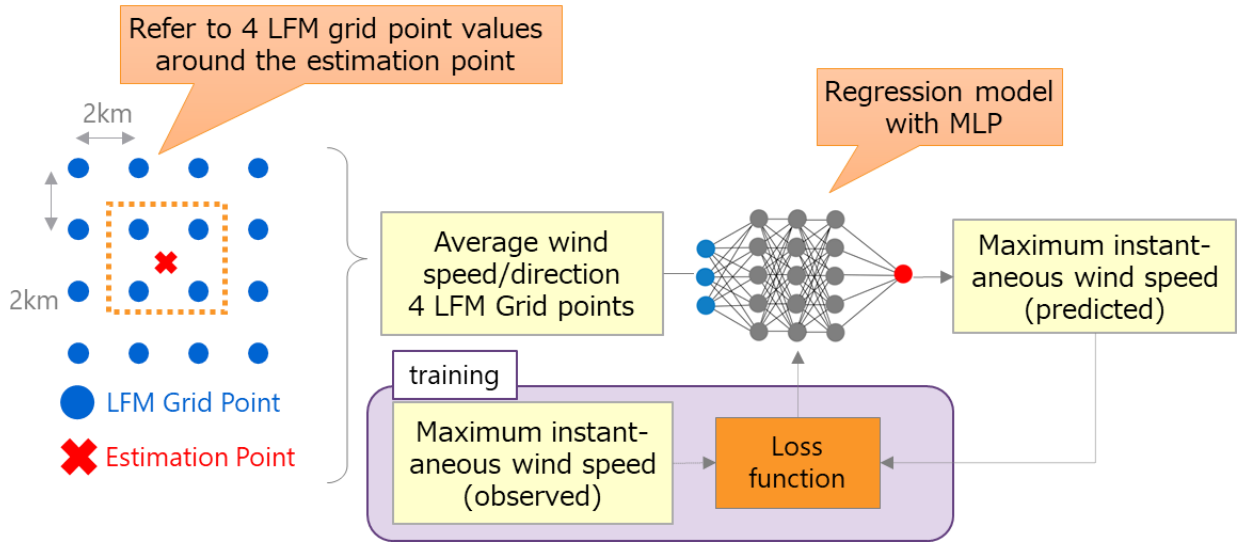

Figure 3 Wind speed forecasts using deep neural network model

4. Comparative Evaluation Using Real Data

Kyushu Railway Company, a Japanese railway operator, provided data on maximum instantaneous wind speeds observed at four locations with anemometers on railway line over about one and a half years. Using this data, we trained regression models and evaluated forecast accuracy. We applied both the fluid analysis-based and AI-based wind speed forecast methods to this data. The LFM data was converted to 10-minute intervals by linear interpolation, and the forecasting methods were applied to the LFM data.

Figure 4 shows an example of the maximum instantaneous wind speed observed by an anemometer and forecasted by fluid analysis-based and AI-based methods for three days from 27th to 30th March. The horizontal axis represents the date and time, while the vertical axis represents the maximum instantaneous wind speed [m/s], the solid blue line indicates the observed value, the solid orange line represents the value

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forecasted by the fluid analysis method, the solid green line represents the value forecasted by the AI method, and the black dashed line indicates the wind direction at LFM. Both the fluid analysis-based and AI-based methods effectively capture the trend of wind speed fluctuations, and their absolute wind speed values align closely. However, the fluid analysis-based method showed a large discrepancy in the forecast results during the time period around 22.5°, when the LFM's wind direction was north-northeast, suggesting that there was some factor that caused the wind speed distribution calculated by the fluid analysis to be different from the actual one for the northeast wind direction. On the other hand, the AI-based method was able to learn the characteristics of the actual wind conditions from the measured wind speeds, and thus did not produce significant errors.

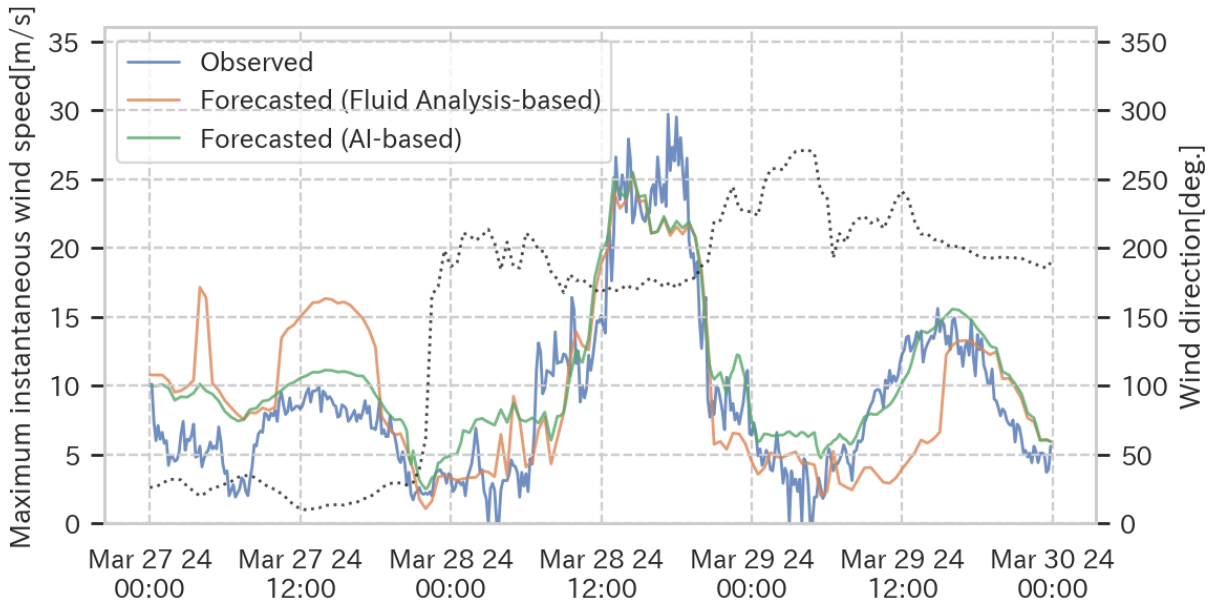

Figure 4 Time Series Graph of Measured and Forecasted Maximum Instantaneous Wind Speeds

Figure 5 shows the results of the root mean square error (RMSE) evaluation of the forecast accuracy for maximum instantaneous wind speeds of 10 [m/s] or higher, assuming strong winds, using data from four locations of about six months (the other one year of data was used as training data). The orange bars indicate the fluid analysis-based maximum instantaneous wind speed forecast error, and the green bars indicate the AI-based maximum instantaneous wind speed forecast error. The target value of the maximum instantaneous wind speed forecast error is set to be less than 5 [m/s] (red dotted line), given that the operating regulation value for strong winds is generally set at every 5 [m/s].

It can be confirmed that both methods achieve the target value of the maximum instantaneous wind speed forecast error. Comparing the fluid analysis-based method and the AI-based method, it can be confirmed that the AI-based method has a 30-40% smaller error in forecasting the maximum instantaneous wind speed. The reason for this is thought to be that the fluid analysis-based method could not accurately evaluate the wind speed distribution because the topography and building models and analysis boundary condition settings differed from the actual environment under some conditions during the wind resource analysis. On the other hand, the AI-based method, for example, is considered to be able to forecast without any problems even when affected by unexpected structures that are not included in the topography and building models, because it learns patterns from actual measured data.

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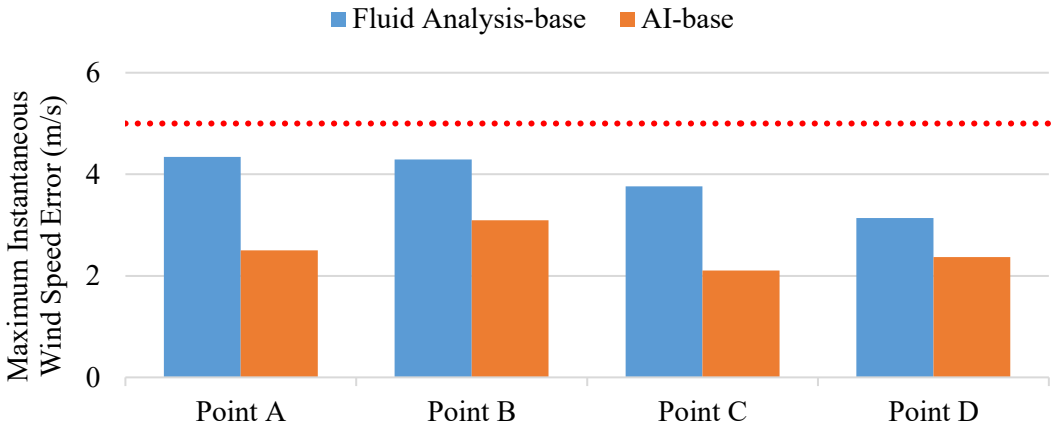

Figure 5 Results of maximum instantaneous wind speed forecast error

5. Conclusion

We examined a fluid analysis-based method and an AI-based method for forecasting the maximum instantaneous wind speed in a strong wind forecast system for railway operations. We evaluated the accuracy of the fluid analysis-based method and the AI-based method using actual wind data from railway lines. The fluid analysis-based method does not require observed wind speeds and can forecast at arbitrary points, while the AI-based method requires observed wind speeds and can only forecast at points where observed wind speeds are available. In cases where observed wind speeds cannot be obtained, the fluid analysis-based method is the only option. However, in cases where actual wind speeds can be obtained, it was confirmed that the AI-based forecasting method in this case reduces forecast errors by about 30-40% compared to the fluid analysis-based forecasting method, and it is preferable to choose the AI-based forecasting method.

We will focus on developing a hybrid forecasting method that incorporates the advantages of both approaches, aiming to achieve more extensive and accurate forecasts in the future.

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