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An accurate hybrid intelligent approach for forecasting flicker severity caused by electric arc furnaces

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ABSTRACT

Drastic variations of reactive power consumed by electric arc furnaces (EAFs) often lead to significant voltage fluctuations at the connecting network bus and yield noticeable flickers of lighting devices as well as cause malfunctions of the electrical equipment. If the flicker severity levels are predictable, corrective solutions such as controls of EAF electrodes and reactive power compensators can be developed to mitigate the voltage fluctuations. This paper presents a hybrid approach that combines an improved radial basis function neural network (IRBFNN) and Grey model for the forecast of flicker severity levels. Field measurements are used to train and implement the forecasting model. Test results of ΔV_{10}, short-term flicker severity (P_{st}) and long-term flicker severity (P_{lt}) obtained by the proposed and five other methods are then under comparisons. Results indicate that more accurate flicker forecast is obtained by adopting the proposed method.

1. Introduction

Rapid fluctuating voltages associated with drastic reactive power consumptions of electric arc furnace loads often cause noticeable flickers of lighting devices and malfunctions of the electrical equipment. With the increasing installation of nonlinear loads such as electric arc furnaces and distributed energy resources, it shows that voltage fluctuations and flicker problems frequently occur in the power network. Thus, a precise forecast of flicker severity level is of great importance for the design or implementation of voltage fluctuation mitigation strategies and flicker planning.

In general, EAF loads have seasonal electric power contract with the local electric utility and often operate full-time over weekends and only during night time (i.e. low system load hours) over weekdays. Therefore, the power consumption and voltage fluctuation patterns at the EAF connecting bus are periodic with stochastic and non-stationary variations. Not like the commonly seen short-term (1–7 days) load forecast problems that the load level is typically periodic and slow changing over time, forecasting flicker severity associated with the voltage fluctuation over the same time horizon is more difficult to be precisely predicted. Other forecasting problems related to wind power or photovoltaic output involves the intermittent and stochastic nature with several different time horizons under considerations. Forecasting both types of renewable energy output present even more challenges. Because non-periodic voltage fluctuation and flicker severity patterns are usually caused by the EAF in maintenance or system faults during the EAF operation and are not in the scope of the forecasting study.

To tackle the problems associated with drastic voltage fluctuations, many approaches have been proposed to assess the flicker severity. For example, the wavelet transform and fuzzy linear estimation were adopted to evaluate flicker severities corresponding to voltage fluctuations [1,2]. The dynamic EAF modeling for flicker planning associated with voltage fluctuations based on modulating the EAF arc resistance or voltage with sinusoidal and band-limited white noise variations and chaos theory-based methods were proposed in [3–6]. The models developed by these methods can be used to simulate the voltage fluctuations due to the EAF in operation and the flicker severity can be assessed.

Alternatively, forecasting methods can be implemented to predict flicker severities according to actual measured data. Traditional forecasting methods include the unit variant that adopts historical data, the multi-variant that uses the relationship among many variants, and qualitative evaluations that use individual judgments [7]. These forecasting approaches are established to predict data trends over selected time horizons. Nevertheless, substantial forecast differences are observed due to different time intervals being considered when applying these approaches. For instance, unit variant methods typically produce better accuracy for short-term forecasts. Though the traditional statistical forecasting methods are

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able to give satisfactory prediction results, however, they suffer the need of collecting significant amount of relevant information for many prior assumptions of the model and are not easy to be applied [8,9].

Though traditional forecasting methods based on regression analysis, such as autoregressive moving average (ARMA) or autoregressive integrated moving average (ARIMA), have the advantages of matured technology and easy implementation; however, they are based on linear analysis and usually cannot forecast the nonlinear data series accurately. To prevent the drawbacks of the regression-based methods, artificial intelligence-based and hybrid forecast engine methods have gained attention for forecasting applications in recent years. Some of the new methods include neural network-, Grey model-, enhanced differential evolution and neural network-, and support vector regression-based RBFNN approaches. Application experiences have shown that the new models outperform the classic models in forecasting accuracy [10–18].

To assess or to forecast the EAF operation behaviors, literature surveys show that several neural network-based methods have been proposed [19–21]. However, the applications for forecasting flicker severity levels associated with EAFs in operation are rarely found. In [22] and [23], the authors have proposed a procedure for predicting the flicker index, ΔV_{10}, by an improved Grey model-based method and the traditional radial basis function neural network (RBFNN) for individual DC or AC EAF in operation. The pitfall of the proposed methods for the flicker severity index, P_{st} (and P_{lt}), is that the index is more difficult to precisely predict than ΔV_{10} because it is statistically calculated in longer time segments of 10 min and thus produces more irregularities and uncertainties in the data series. Also, the proposed methods for the forecast of flicker severity involved two different types of EAFs (i.e. DC and AC) simultaneously operating lead to less accurate results than that for individual EAF in operation. To increase the prediction accuracy, this paper proposes a hybrid approach based on the integration of Grey model and an improved radial basis function neural network (IRBFNN) method that is suitable for flicker severity forecast of both ΔV_{10} and P_{st}, regardless of either individually operated EAF or different types of EAFs under simultaneously operations.

The conventional RBFNN algorithm has a wide range of applications in model identification, time series prediction, and other research fields [24]. When applying RBFNN for forecasting, the challenges are that it is not easy to decide the number of hidden-layer neurons in RBFNN and the parameters of the center and standard deviation associated with the Gaussian basis function for each neuron. The center and standard deviation of the Gaussian basis function are useful for supervised and unsupervised learning decisions. Many approaches have been proposed to effectively determine these parameters. For instance, the supervised learning using K-means algorithm can be adopted to find cluster centers of the Gaussian basis functions of all neurons in the hidden layer and then to use the nearest neighboring rule to determine the appropriate size of each standard deviation [25]. Also, the initial center value for each basis function can be randomly selected. However, the RBFNN has a disadvantage that all parameters to be determined have equal weights, which affect the training convergence and the solution accuracy.

In the proposed hybrid approach, the Grey model deals with grey systems that are characterized by both partially known and partially unknown information, and the IRBFNN includes a new parameter of the weight in the Gaussian basis function to improve the convergence and solution accuracy of the neural network training algorithm. To verify whether the proposed method provides more accurate forecasts than the conventional RBFNN and the other methods under comparisons. Test cases of flicker severity forecasts for ΔV_{10} and P_{st} (and P_{lt}) associated with different types of EAF

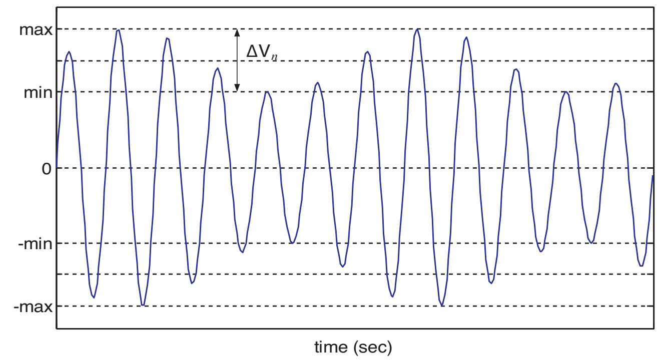

Fig. 1. Sinusoidal voltage fluctuation.

plants (i.e. DC and AC EAFs) are performed. Forecasted results show that the proposed Grey-IRBFNN approach is superior to the back-propagation neural network (BPNN) [12], the conventional RBFNN [18], and the Grey model-based model [11,22].

The organization of the paper is as follows. Section 2 introduces the definitions of flicker severities, ΔV_{10}, P_{st} and P_{lt}, corresponding to EAF loads is described. The Grey model and proposed IRBFNN is then described and the solution procedure of training and recalling processes of the neural network for forecasting the flicker severity is addressed in Section 3. Section 4 illustrates test results to show the superiority of the proposed method over other compared approaches and is followed by the conclusion of Section 5.

2. Flicker severity indices

Flicker is used to describe the impression of unsteadiness of visual sensation induced by a light source whose luminance or spectral distribution fluctuates with time. To quantify the flicker severity due to the low-frequency components, typically in the range of 0.1–30 Hz, of the fluctuated voltage is of importance for flicker mitigation or planning. In general, the fluctuated voltage can be expressed by the amplitude modulated signal given in (1):

$$v(t) = \left[A_0 + \sum_{i=1}^{m} A_i \ \cos(\omega_{fi} t + \phi_{fi}) \right] \cos(\omega_0 t + \phi_0) \tag{1}$$

where A_0, ω_0, ϕ_0, A_i, ω_{f_i}, and ϕ_i, are amplitudes, angular frequencies, and phase angles of the fundamental and flicker components, respectively. m is the total number of flicker components. For the voltage fluctuation amplitude at the nth frequency bin, ΔV_n, it can be defined by

$$\Delta V_n = \frac{V_{p,\max} - V_{p,\min}}{V_p} \times 100\% \tag{2}$$

where V_p is the nominal fundamental peak voltage. $V_{p,max}$ and $V_{p,min}$ are the maximum and minimum peak values of the fluctuated voltage signal, as shown in Fig. 1.

There are two commonly used indices that have been proposed for the assessment of flicker severities. In several Asian countries, the index of ΔV_{10} established by Central Research Institute of the Electric Power Industry in Japan is often adopted to evaluate the flicker severity caused by electric arc furnaces [26]. The voltage fluctuation (characterized from 0.1 Hz to 30 Hz) at 10-Hz equivalent value, ΔV_{10}, is defined as the flicker severity level of

$$\Delta V_{10} = \sqrt{\sum_n (a_n \cdot \Delta V_n)^2} \tag{3}$$

where ΔV_n stands for the fluctuation amplitude of the specified nth frequency bin and a_n is the equivalent sensitivity coefficient of the corresponding nth frequency component corresponding to 10 Hz.