A DTW Based Automatic Transient Identification Method in Nuclear Power Plants

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INTRODUCTION

In nuclear power plants (NPPs), the transient identification is significant for the monitor of fatigue damage of piping and components. During the design of the NPPs, the design transients are characterized by the time series data of temperature, pressure and flow rate. However, the operational transients are usually different from the design transients during the service of NPPs. Since there are various reasons that cause the discrepancies between the design transients and the operational transients, how to identify an operational transient and classify it into the design transients is a challenged problem. [1-3]

The transient identification method can be categorized into model-based method and model-free method. The main idea of model-based method is using mathematical models to describe and measure the transients. The model-free methods do not rely on explicit mathematical models of a concerned system and seems to be more appropriate for transient identification in NPPs.

In present work, a Dynamic Time Warping (DTW) based model-free method is proposed. In this method, the time series data of temperature, pressure and flow rate obtained from sensors are used as input data. Then Dynamic Time Warping (DTW) is used to calculate the similarity between the data of sensor and the data of design transients. With a combination of the similarity for temperature, pressure and flow rate, the present transient can be classified into one design transients effectively.

The transients of China's 3rd-generation nuclear power plant - HPR1000 are used to verify present method. The results show that more than 95% transients can be classified into design transients correctly.

THE TRANSIENT IDENTIFICATION METHOD

The Dynamic Time Warping (DTW) Algorithm

The dynamic time warping (DTW) is an algorithm for measuring similarity between two time series,[4] which may vary in speed. DTW has been applied to many field associated with linear sequence data. A well-known application of DTW algorithm is the automatic speech recognition, to cope with different speaking speeds. Other applications include speaker recognition and online signature recognition. Also it is seen that it can be used in partial shape matching application.

In general, DTW is a method that calculates an optimal match between two given sequences (e.g. time series) with certain restrictions. The sequences are "warped" non-linearly in the time dimension to determine a measure of their similarity independent of certain non-linear variations in the time dimension, as shown in Fig.1. Since the "warped" process can normalized the speed and amplitude of two different time sequence, the DTW method is widely used in time series classification.

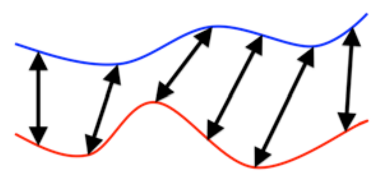

Fig. 1. The schematic of DTW algorithm.

The Transient Classification Method

The sensor data of temperature, pressure and flow rate are included in one operational transient. The operational transient $TR^{op}(t)$ can be described as

$$TR^{op}(t) = [T(t), P(t), F(t)] \tag{1}$$

Where $T(t), P(t), F(t)$ are the time series of temperature, pressure and flow rate measured from various sensors, respectively.

Meanwhile, the design transients $TR_n^{de}(t)$ are described as

$$TR_n^{de}(t) = [T_n(t), P_n(t), F_n(t)], \quad n = [1, N] \tag{2}$$

Where n is the index number of present transient in the design transients list; N is the total number of transients list; $T_n(t), P_n(t), F_n(t)$ are the time series of temperature, pressure and flow rate for present transient, respectively.

The DTW algorithm is employed to calculate the similarities between $T(t), P(t), F(t)$ and the N-th design transients $T_n(t), P_n(t), F_n(t)$, respectively. The result can be written as

$$S_n = [S_n^T, S_n^P, S_n^F], \quad n = [1, N] \tag{3}$$

Where n represent the similarity between n-th design transient and the operational transient, the components S_n^T, S_n^P, S_n^F can be calculate by

$$S_n^X = DTW\left[X(t), X_n(t)\right], \quad X = T, P, F \qquad (4)$$

Where the T, P, F represent the temperature, pressure and flow rate, respectively.

To consider the different contributions of these components T, P, F during the classification of transients, the contribution factor is introduced in present work. The effective similarity $\overline{S}_n$ can be written as

$$\overline{S}_n = \sqrt{\lambda^T (S_n^T)^2 + \lambda^P (S_n^P)^2 + \lambda^F (S_n^F)^2}, \quad n = [1, N] \ (5)$$

Where λ^T , λ^P and λ^F are the contribution factors for temperature, pressure and flow rate, respectively. These contribution factors are identified during the initialization. Usually, the contribution of temperature to the classification is the largest, the pressure is the second one, and the flow rate has slight contribution.

To identify the unknown transients, which cannot be classified into any design transient, a threshold value $\overline{S}_n'$ for effective similarity $\overline{S}_n$ is introduced in present work. Once the effective similarity $\overline{S}_n$ is large than the threshold value $\overline{S}_n'$, the transient is identified as a unknown transient. Notes that the threshold value $\overline{S}_n'$ and the contribution factors $\lambda^T, \lambda^P, \lambda^F$ are flexible parameters for adjustment. These parameters can be determined by a training process with some labeled transients as inputs.

The Online Identification Process

The flowchart of the online transient identification process is shown in Fig. 2. It should be notice that the transients dataset in present method is not a constant one.

At the beginning of the serve life of the NPP, since no operational transient occurs, the transients dataset only include the design transients (coming from numerical model). Once an operational transient occurs, the DTW algorithm is used to calculate the similarity between the data measured by sensor and corresponding data in transients dataset. If the new transient can be classified into known design transient, the transients dataset is updated by add the new operational transient to the transients dataset. Thus, the design transients and classified operational transients are included in the updated dataset for further classification process. If the new transient cannot be classified into known design transient, the transient dataset is updated by increasing a new type transient.

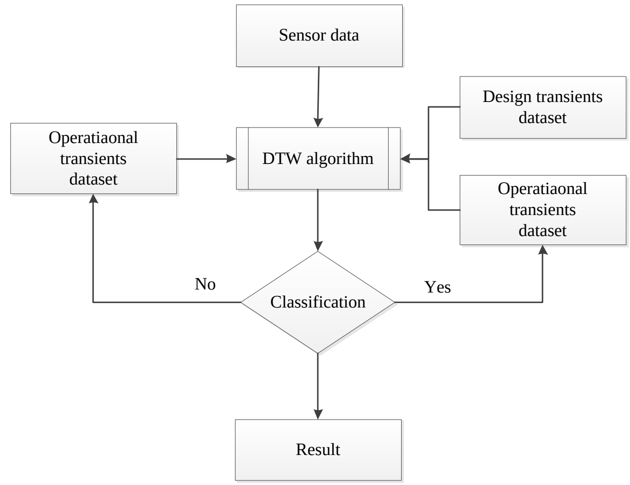

Fig. 2. Flowchart of the DTW based transient identification method.

RESULTS AND DISCUSSIONS

The transients of China's 3rd-generation nuclear power plant -HPR1000 are used to verify present method. The initial transients' dataset is construct by 40 design transients of HPR1000. Since no operational data is available, 500 artificial transients with labels are used as the input data for the verification. The effect of flow rate is ignored in present work. In the verification, more than 95% transients can be identified correctly. An example is shown in Fig. 3 and Fig. 4. The local view and global view of the DTW distance for temperature and pressure is shown in Fig. 3. It can be seen the DTW distance between present transient and the correct target transient (No.30) is very small. Meanwhile, the distance between present transient and other transients are relatively large. The temperature and pressure data for No.30 design transients and the present transient is compared in Fig. 4. It can be observed that although the duration and the variation form of design transient and present one is different. The present transient can be identified correctly.

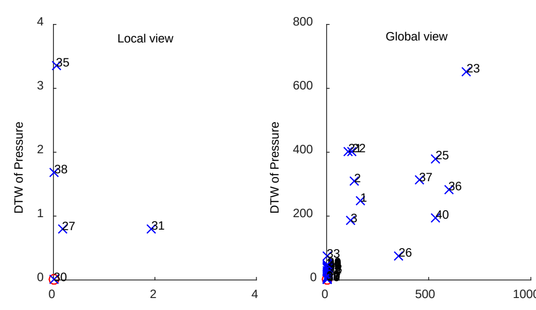

Fig. 3. The DTW distances of temperature and pressure.

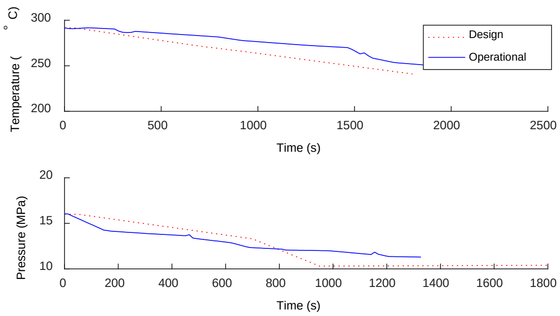

Fig. 4. The comparison between design transients and operational transients.

CONCLUSION

A dynamic time warping (DTW) based automatic transient identification method is proposed in present work. The advantage of present method is that few training data is necessary, which is very important for the new NPPs like China's 3rd-generation nuclear power plant HPR1000. Meanwhile, the new occurred operational transients can be absorbed into the dataset during the identification. These will significant increase the accuracy for the further identification.

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