Development of Fast Simulation Technique using Deep Autoregressive Model

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1. Introduction

A probabilistic safety assessment (PSA) has been used to estimate the risk of nuclear power plants (NPPs). To traditional approach to analyze the PSA is Event Tree and Fault Tree (ET/FT). Though there are many advantages of ET/FT methodology, it is natural to anticipate that the traditional PSA techniques based on ETs and FTs intrinsically has high uncertainties sources, such as parameter uncertainty and model uncertainty [1].

To reduce uncertainty of PSA, the ETs has more diversity to branch points considering time, operator action, and multiple branch. However, the problem is that the number of scenarios to be analyzed by precise thermal-hydraulic (TH) codes will drastically increase for a complicated system containing many systems or components. Since each run of the precise TH code generally takes several hours to a day, it is evident that a technique for determining the consequence of each plausible scenario within a short time period is the key to reduce PSA uncertainties.

In order to resolve this problem, the deep learning techniques is introduced in previous study. One of the key benefits expecting from these deep learning techniques is that it is possible to create an emulation system that can synchronize the repose (or behavior) of a target system. The suggested techniques are also called a surrogate model or a fast running. In the previous study, feasibility study that the deep learning technic is able to emulate TH code was carried out.

2. Methods and Results

This chapter describes deep autoregressive mod and results. In deep autoregressive model which is wavenet specifically is described. After that, the results of fast simulation using wavenet is described.

2.1 Deep Autoregressive Model

In terms of developing a deep learning model, similar to all kinds of data-driven models, one critical process is to understand the characteristics of the datasets to be represented by the model. In this regard, the characteristics of the results from a precise TH code, which are needed to analyze the result of each accident scenario, is autoregressive feature. The TH results provide the trend of process parameters (e.g., the temperature of a reactor coolant system) as time goes by. The autoregressive data indicates that the value of the current time step is the output of the previous time step. The autoregressive feature consists of the joint probability of a time series $\mathrm{x} = \{x_1, \cdots, x_T\}$. This feature can be understood by the following equation:

$$x_t = c + \sum_{i=1}^{p} \varphi_i x_{t-i} + \varepsilon_t \tag{2.1}$$

where $\varphi_1, \cdots, \varphi_p$ are the model parameters, c is a constant, and ε_t is white noise. In other words, the autoregressive model is that the errors are cumulative when it forecast the multi-step. Among deep learning model, the discriminative model that classifies the label based on decision boundary is able to have low accuracy due to accumulation of the error. The autoregressive feature is expressed the joint probability form that is factorized as a product of conditional probabilities as follows:

$$p(\mathrm{x}) = \prod_{t=1}^{T} p(x_t \mid x_1, \cdots, x_{t-1}) \tag{2.2}$$

There many researches have been studied to representative autoregressive feature [2, 3]. Among these research, the wavenet is selected in this paper. The wavenet shows the remarkable performance in deep autoregressive model. Most of the previous studies used recurrent neural networks for time series prediction, but wavenet predicted time series using convolutional layers. Figure 1 shows 1-dimension convolutional layer. The 1-D convolutional layer performs two stage for making receptive filed: 1) make arbitrary filters and 2) calculate element-wise product and summation.

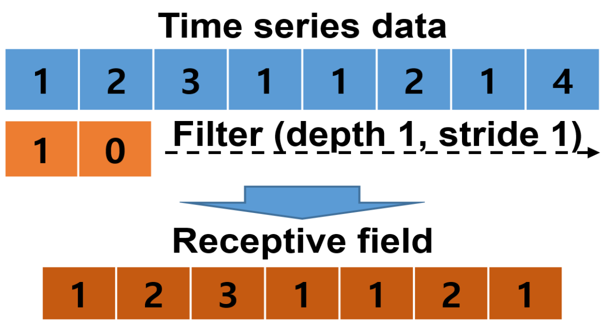

Fig. 1. 1-Dimension convolutional layer

In figure 1, the filter is expressed as a 1 depth filter, thus a receptive filed is calculated. Generally, numerous filters are used in a general deep learning model depending on data size. In addition, causal convolutional layers are used. Even though the model is deeper, the 1-D convolutional layers are difficult to keep the time series connection. Thus, to handle time series connection in hidden layers, the wavenet uses the causal convolutional layers to express the autoregressive feature. Figure 2 shows a stack of causal convolutional layers.

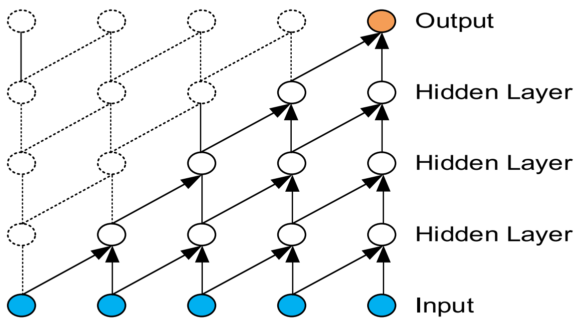

Fig. 2. Visualization of a stack of causal convolutional layers

When the 1-D causal convolutional layers are used, the receptive filed is heavy to calculate and take long calculating time. Thus, to avoid this effect, the dilation rate is used in hidden layers. The dilation rate expands the filter size as figure 3. As seen in figure 3, the filter size is expanded and filled the zeros between original filter data. When the dilation rate adopted, the receptive fields are calculated by sparse filter. Generally, the results of TH code is important to trend than every time step. The input layer recognizes all time step, the hidden layer recognizes sparse time step, however, keeps the correlation in time step. In addition, this method is able to avoid the accumulation of errors.

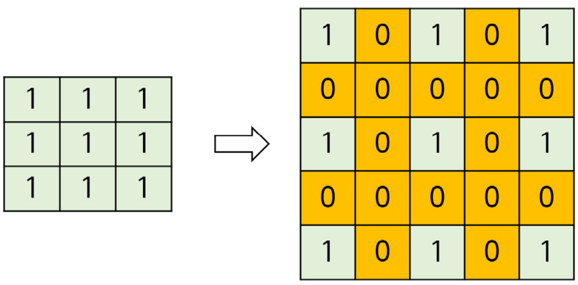

Fig. 3. Conceptual diagram dilation rate in 2-D convolutional layer (Dilation rate=2)

In addition to this, wavenet designed and applied skip connection and gated activation unit. The gated activation unit used in wavenet is shown in Figure 4.

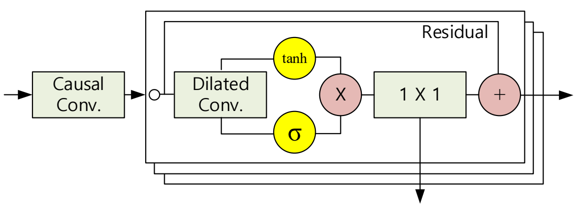

Fig. 4. Schematic Diagram of Gated Activation Unit

2.2 Results

In order to show the effect on 1-D convolutional layer, an analysis of 10-time steps prediction is performed. Figures 5 and 6 show results of the LSTM cell and 1-D convolutional layer, respectively. The accuracy of LSTM is 2.38%, the accuracy of the 1-D convolutional layer is 0.69%. As shown in Figures 5 and 6, it can be seen that the accuracy of 1-D convolutional layer is higher.

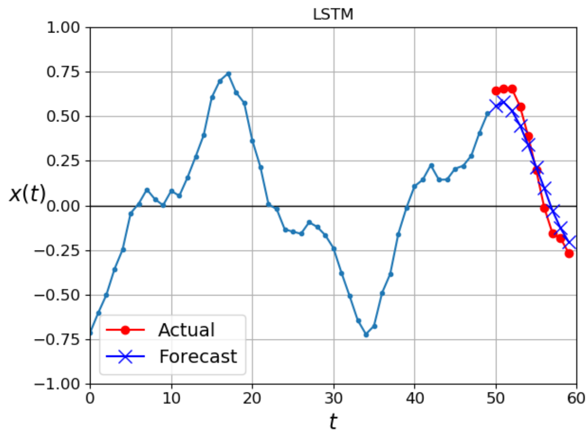

Fig. 5. 10 time steps prediction using LSTM cell

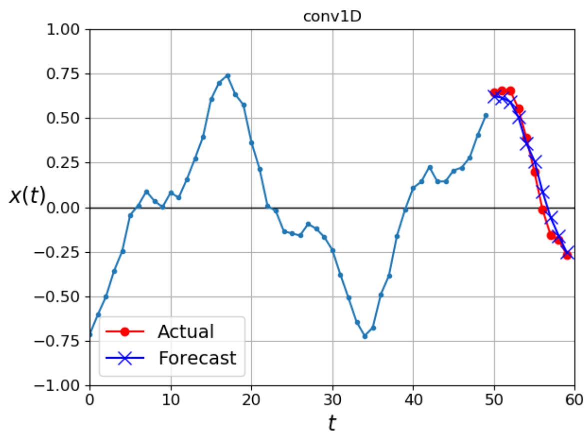

Fig. 6. 10 time steps prediction using the conv1D

3. Conclusions

In this paper, a deep autoregressive model is proposed for fast simulation of TH code. The proposed model is based on wavenet. In this study, we compared LSTM and the 10-time step prediction of the proposed model. In a future study, the accuracy of the proposed model for long-distance prediction using real TH data should be evaluated.

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