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Toward the use of deep learning techniques to enhance PSA quality: A digital twin

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1. Introduction

One of the recent research trends observable from many different domains or industries is the use of diverse deep learning techniques [1-7]. As a branch of machine learning, the deep learning techniques are not novel because their start can be back to 1940s [8]. However, since 2006, the deep learning techniques have become very popular because of several reasons, such as increasing computing power, increasing data size, and advancing deep learning research [9]. Of them, the breakthrough of deep learning techniques is remarkable, which results in the development of amazing variants including auto-encoders, deep belief networks, deep Boltzmann machine, convolutional neural networks, and recurrent neural networks [8-10]. For example, in terms of a machine health monitoring system (MHMS) development, which is one of the major application domains considered in the machine learning, Zhao et al. emphasized that the role of deep learning techniques is to replace a part of the MHMS instead of switching its whole part (Fig. 1).

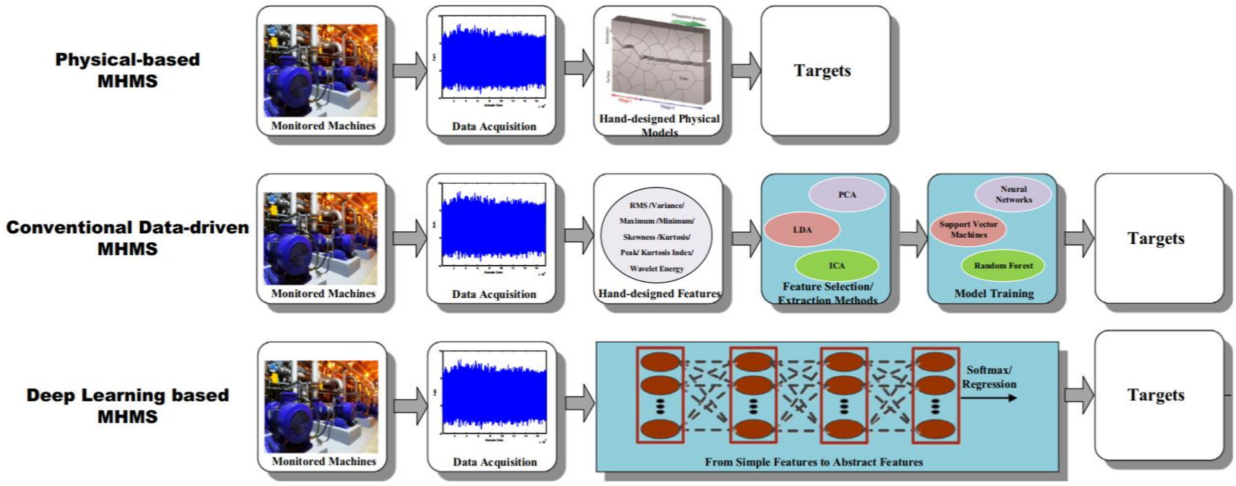

Figure 1. Role of deep learning techniques, adopted from Ref. [9]

For example, in order to implement a MHMS, principal component analysis (PCA) techniques and support vector machines (SVMs) belonging the category of machine learning techniques have been traditionally used for many decades, which extensively require the manual intervention of developers, such as manual feature extractions, manual transformations, and model trainings. In contrast, an MHMS developed by the combination of deep learning techniques provides a seamless process that does not demand the manual interventions. This implies that the applicability (or application domain) of deep learning techniques should be searched from the standpoint of 'enhancing existing techniques' instead of 'replacing existing techniques.' In this regard, this study proposes the use of a digital twin that could be helpful for reducing uncertainties through resolving one of fundamental issues about the estimation of probabilistic safety assessment (PSA) results.

2. Underlying limitations of PSA technique

A PSA technique has been used for several decades to visualize the risk level of commercial nuclear power plants (NPPs). According to the statement of U.S. Nuclear Regulatory Commission (NRC), PSA can be referred to as: "The method or approach (1) provides a quantitative assessment of the identified risk in terms of scenarios that result in undesired consequences (e.g., core damage or a large early release) and their frequencies, and (2) is comprised of specific technical elements in performing the quantification [11]." According to this statement, the critical part of the PSA technique is to identify, as realistic as possible, plausible accident scenarios with associated frequencies that can cause undesired consequences (e.g., core damage or large early release frequency).

For example, let us assume that there is an arbitrary system that consists of three key components (*A*, *B*, and *C*) with two possible states (*Success* and *Failure*). This means that the total number of observable scenarios from the system is eight. Of them, if an accident happens when two or more components are failed, the number of accident scenarios that are related the system's risk become four. Accordingly, in terms of quantifying the system's risk, one of the promising approaches is to sum up failure frequencies calculated from all accident scenarios [12].

The problem is that, however, the number of accident scenarios will drastically increase for a complicated system that comprises of a lot of components, such as petro-chemical plants and NPPs. This means that we need to put huge amount of resources on the analysis of a thermal-hydraulic (TH) code that tells the consequence of each accident scenario. More serious problem is that the current PSA technique does not consider the dynamics of different component failure timings, which resulted from interactions among diverse process variables (pressure, temperature, coolant flow, etc.), automated actions (automatic start of a pump when a specific set-point exceeded), and human actions (turn on a pump, close a valve, start a heater, etc.). As a result, in reality, the number of accident scenarios to be assessed exceeds controllable range along with the evolution of process variables, automated actions, and human actions [13, 14]. For this reason, various assumptions are incorporated into PSA techniques, which are effective to reduce the number of accident scenarios into a manageable range. Consequently, it is evident that one of the primary sources related to the epistemic uncertainty of PSA results is due to the reduction of accident scenarios (Fig. 2).

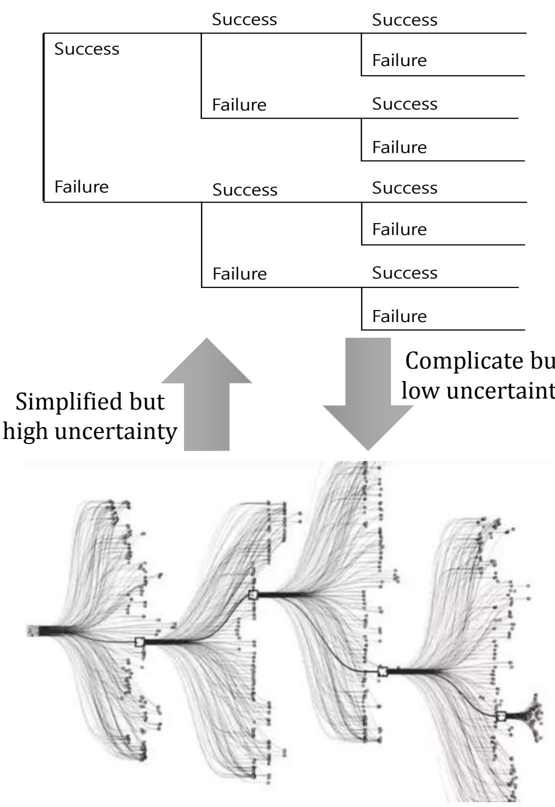

Figure 2. Uncertainty source of PSA results

3. Development of a digital twin based on deep learning techniques

As explained at the end of the previous section, the more the reduction of accident sequences increases the more the uncertainty of PSA results increases. In this regard, a digital twin developed by the combination of diverse deep learning techniques could be the solution of this problem. According to GE, the digital twin is "an organized collection of physics-based methods and advanced analytics that is used to model the present state of every asset in a Digital Power Plant. […] Included in the Digital Twin models are all necessary aspects of the physical asset or larger system including thermal, mechanical, electrical, chemical, fluid dynamic, material, lifting, economic and statistical. These models also accurately represent the plant or fleet under a large number of variations related to operation [15]." That is, the most important benefit of the digital twin is the provision of a digital replica for a target system, which allows us not only to continuously monitor the current state but also to precisely evaluate the future state of the target system. Figure 3 depicts one of the typical applications based on the digital twin.

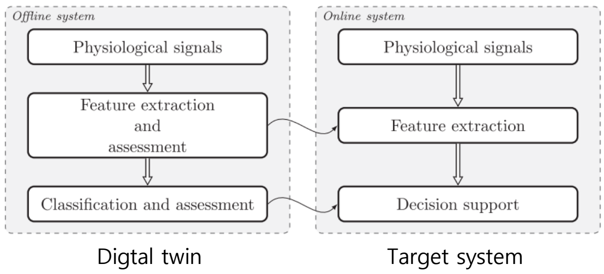

Figure 3. Typical application of digital twin, adopted from Ref. [16]

As can be seen from Fig. 3, its application domain is the on-line healthcare of patients. To this end, it is necessary to develop a digital twin that allows us to characterize the features (premonitory symptoms) of tremendous physiological signals and classify the status (diagnostics) of patients. Once we have this digital twin, it can be used to not only monitor the current condition of patients in real-time but also support medical staff by providing valuable information, such as the expected status of patients or effective emergency measures for them.

Here, it is very interesting to imagine that the uncertainty of PSA results can be significantly reduced if we have the digital twin of a TH code. In general, since the rune time of TH codes for determining the consequence of each accident scenario takes a few hours to several days, it is only possible to analyze a limited number of accident scenarios with limited resources (time and budget). However, if we have a technique to build a digital twin that can soundly emulate the output of a specific TH code in a very short time (e.g., a couple of seconds), it is expected that we are able to analyze tremendous number of accident scenarios without spending huge amount of resources. This means that not only the uncertainty of PSA results can be effectively reduced but also a catalog of new accident scenarios can be distinguished, which were not considered in existing PSA results.

4. Feasibility of digital twin

In order to investigate the feasibility of a digital twin for a TH code, a deep learning model was developed based on a long short-term memory (LSTM) technique. The LSTM technique is a kind of recurrent neural networks (RNNs) that have feedback connections to store both the current and past information. For this reason, RNNs are good at many applications such as speech processing, music composition or interpolating time series data [17, 18]. It should be noted that, although the explanation of detailed technical basis about RNNs would the beyond of this paper, their basic concept is to estimate a future condition. Here is an example for explaining the benefit of RNNs.

In case of estimating the electrical demand of a certain country, it is evident that its value varies along with diverse factors, such as the population, the number of households, the amount of gross domestic product, outdoor temperature, and humidity. The problem is that the development of an electrical demand estimation model is not easy because of complicated causalities among these factors. In addition, this model should be dynamic so that it can properly represent dynamic interactions as time goes by. For example, since the highest and lowest temperature become different in every month, their values of past months are very important for estimating the electrical demand of the next month. In this regard, RNNs are powerful because they are modeled so that their information collected from past months play as inputs to estimate the electrical demand of the next month. Actually, Fig. 4 shows the result of a case study to predict the electrical demand of the whole country based on a LSTM model that was constructed by ten selective factors. As can be seen from Fig. 4, it seems that the LSTM is good at interpolating the trend of the electrical demand.

5. Discussion and conclusion

In terms of reducing the uncertainty of PSA results, it is expected that at least two issues should be technically resolved: (1) identifying accident scenarios as realistic as possible, and (2) evaluating the consequence of accident scenarios. Of them, the first issue can be addressed by applying dynamic PSA techniques that allow us to create diverse accident scenarios after combining various kinds of process parameters, automated actions and human actions.

In addition, it is expected that the second issue can be soundly resolved by adopting deep learning techniques such as a LSTM. In other words, if we are able to develop a digital twin that can provide (or emulate) reliable results of a specific TH code, then it is strongly anticipated that more fast evaluations about the consequence of each accident scenario can be done. In this aspect, this study would be an initial step for developing such digital twin.

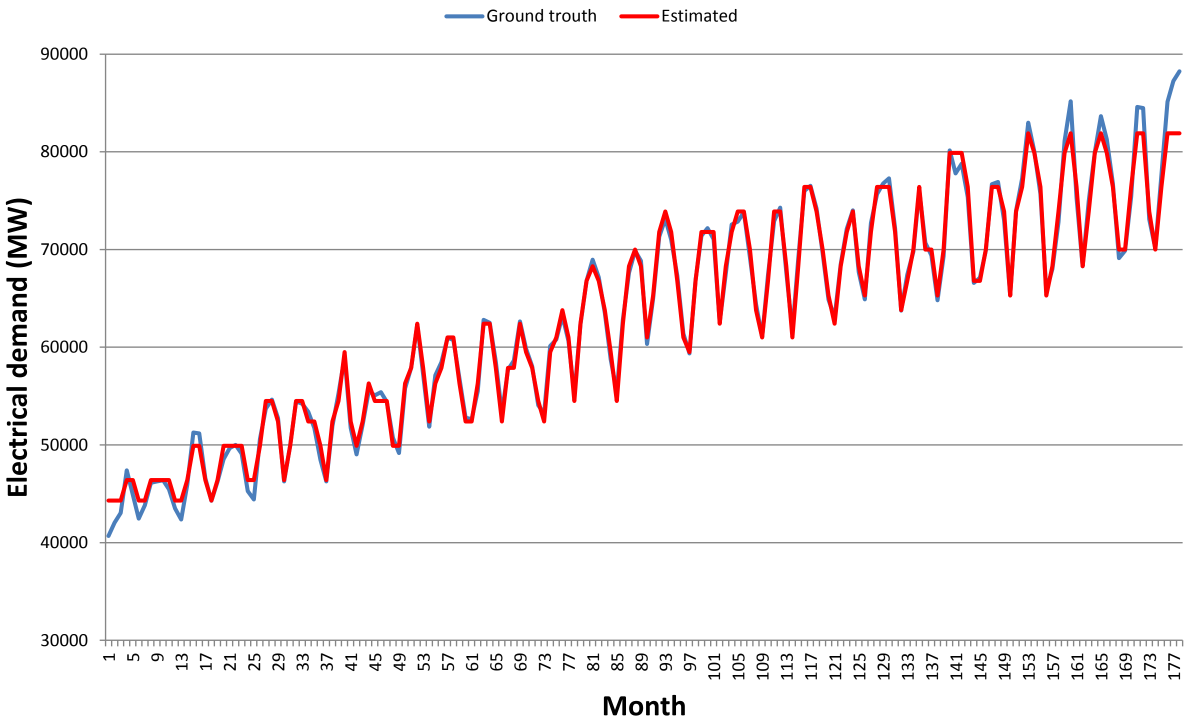

Figure 4. Electrical demands – Comparing ground truth and estimation

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