Abstract

Generative models have been demonstrated to be a powerful way of learning implicit data distribution, which can be applied in many use cases in the power grid such as predictive maintenance, load forecasting, etc. Although generative models are in general computationally intensive, it has been shown in the research community that parameterizing them with deep neural networks and using deep probabilistic programming tools can ameliorate their computational requirement. Thus, this thesis focuses on the use of deep generative models (DGM), in particular, deep Markov model (DMM) and variational autoencoder (VAE) to predict the remaining useful life (RUL) of power system assets. In the proposed approach, we employ the DGM as an embedding network for the reliability model used in predicting the RUL of an asset of interest. We use long short-term memory (LSTM) as the reliability model of the asset's degradation. We compared the result obtained by the proposed approach and those obtained by implementing three different sequence models - recurrent neural network, LSTM, and gated recurrent unit to predict the RUL of the asset. The embedding network was not used in the case of these sequence models. The dataset used in the implementation is the National Aeronautics and Space Administration (NASA)'s Turbofan Engine Degradation Simulation Dataset (version 1) as we were not able to obtain the data set of power system assets such as transformer, inverter, etc. The proposed approach showed superior performance both in fully supervised and semi-supervised settings except in the case where only 5% and 90% label information were used. VAE and LSTM produced better performance in the case when only 5% and 90% labels were used, respectively. Possible future work would be to test the proposed method with an actual power system dataset and also to evaluate the suitability of other generative models such as generative adversarial network and autoregressive flows in RUL prediction task.

Keywords: Predictive maintenance, Generative models, Deep Markov models, Variational autoencoder