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Adaptive online sequential extreme learning machine for frequency-dependent noise data on offshore oil rig

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ABSTRACT

An adaptive online sequential extreme learning machine (AOS-ELM) is proposed to predict the frequency-dependent sound pressure level (SPL) data of various compartments onboard of the offshore platform. With limited samples and sequential data for training during the initial design stage, conventional neural network training gives significant errors and long computing time when it maps the available inputs to sound pressure level for the entire offshore platform. By using AOS-ELM, it allows a gradual increase in the dataset that is hard to obtain during the initial design stage of the offshore platform. The SPL prediction using AOS-ELM has improved with smaller root mean squared error in testing and shorter training time as compared with other types of ELM based learnings and other gradient based methods in neural network training.

1. Introduction

Noise control is required to ensure crew habitability onboard an offshore platform. Applying noise prediction is important to identify the potential noise problem at the early stage of the offshore platform design to avoid costly retrofitting in the implementation stage. The noise in the offshore and marine applications is currently identified using the empirical formula or the computer-aided design (CAD)-based commercial software. The boundary element method (BEM) and Finite element analysis (FEA) analyze the acoustics by considering wave propagation. On the other hand, the statistical energy analysis (SEA) and the energy finite element analysis (EFEA) determine the sound field based on energy flow between subsystems. However, the accuracy of the results could not be guaranteed (Nilsson, 1978) using the empirical formulas on different applications as most could not meet the required shape of the room and sound source as stated in their assumptions. In addition, the CAD-based numerical tool is considered to be quite accurate at certain frequency regime. Unfortunately, using these tools for modeling a large-scale system such as the offshore platform can be quite a time and resource intensive.

For the past few decades, neural networks based learnings have been used to model complex systems with uncertainties. The types of machine learning approaches used in the literature are numerous. In this study, the extreme learning machine (ELM) (Huang et al., 2012) will be used to model the sound pressure level (SPL) on the offshore platform. ELM has become quite useful and necessary for machine learning with its good generalization, fast training time, and universal approximation capability. As compared to other machine learning algorithms such as backpropagation (BP) (Rumelhart et al., 1986), it is well-known that the parameters of hidden layers of the ELM are randomly generated without tuning. The hidden nodes could be determined from the training samples. Huang and his team (Huang et al., 2012, 2006a, 2008; Huang, 2014) have shown that the single layer feedforward networks (SLFNs) (Ding et al., 2015; Huang, 2015; Huang and Babri, 1998; Xu et al., 2017; Yang et al., 2017; Xu et al., 2016; Jia et al., 2016; Oneto et al., 2016; Rafiei et al., 2017; Liang et al., 2006; Tang et al., 2016) ensure its universal approximation capability without changing the hidden layer parameters. ELM using regularized least squares could compute faster than the quadratic programming approach in gradient method adopted by BP. There is no issue of local minimal and instabilities caused by different learning rate, and differentiable activation function.

There are numerous types of ELM learning algorithms. The list in this paper is not exhaustive. A few selected algorithms will be used as shown below. Basic incremental ELM (I-ELM) (Huang et al., 2006a; Huang and Chen, 2007) randomly produces the hidden nodes and analytically computes the output weights of SLFNs. I-ELM does not recompute the output weights of all the existing nodes when a new node is appended. The output weights of the existing nodes are then recalculated based on a convex optimization method when a new hidden node is randomly added one at each time. The learning time for I-ELM is longer than ELM as it needs to compute n output weights one at a time when n hidden

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nodes are used. However, ELM only computes n output weights once when n hidden nodes are used. Few methods using different growth mechanism of hidden nodes were adopted. They are namely enhanced incremental ELM (EI-ELM) (Huang and Chen, 2008), error-minimized ELM (EM-ELM) (Feng et al., 2009) and optimal pruned ELM (OP-ELM) (Miche et al., 2010) that produce a more compact network and faster convergence speed than the basic I-ELM. Another incremental ELM named Bidirectional ELM (B-ELM) (Yang et al., 2012) with some hidden nodes not randomly selected could improve the error at initial learning stage at the expense of higher training time when compared to ELM. Another ELM learning using hierarchical ELM (H-ELM) (Tang et al., 2016) improves the learning performance of the original ELM due to its excellent training efficiency, but it increases the training time due to deep feature learning.

On the other hand, the sequential learning algorithms are quite useful for feedforward networks with RBF nodes (Liang et al., 2006; Platt, 1991; Kadirkamanathan and Niranjan, 1993; Yingwei et al., 1997; Wen et al., 2017; Huang et al., 2004, 2005). Some researchers (Huang et al., 2004, 2005) have simplified the sequential learning algorithms to enhance the training time, but it remains quite slow since data are handled one at a time instead of in batches. The online sequential extreme learning machine (OS-ELM) that can handle additive nodes (and RBF) in a unified framework from the batch learning ELM (Huang et al., 2006a, 2004; Zhang et al., 2018; Huang et al., 2006b, c; Li and Yang, 2017; Budiman et al., 2016) is implemented in SLFNs. As compared to other sequential learning algorithms using different tuning parameters, OS-ELM requires the number of hidden nodes for tuning the networks solely. The newly arrived block or single observation (instead of the entire past data) are learned and removed once the learning process is accomplished. The input weights (connections between the input nodes to hidden nodes) and biases are randomly produced, and the output weights are analytically computed.

Many applications including the noise related applications (Xu et al., 2004; Liu et al., 2014; Nannariello and Fricke, 2001; Aliabadi et al., 2013; Nannariello et al., 2001) have used the neural network in the field of room acoustics modeling. In the current literature, AOS-ELM application to model the sound pressure level in different rooms on board of the offshore platform such as a jack-up rig has not been discussed. The use of steels for room construction in the jack-up rig differs from most of the land-based industrial and acoustic rooms (Hodgson, 2003; Ji and Chin, 2015) as the steel structures increase the percentage of structure-borne noise from 125 Hz to 8000 Hz. There exists no single model that considers the frequency variation, room's geometry, source's power, source(s) position and receiver(s) location in the acoustics model. The application of AOS-ELM is also advantageous due to its ability to converge quickly and sequentially with good generalization. It is useful for SPL modeling during the initial design stage where the data is progressively available in batches with small sample size from different technical teams and vendors in the company. Moreover, the availability of data for the design variables is often delayed by a lack of exact information during the early design stage that makes the sequential ELM based learning which is crafted to handle newly arrived block or single observation whenever the data are available.

This paper has the following sections. Section 2 describes the input and output variables selection for training. Section 3, review on ELM and adaptive sequential ELM learnings on the frequency dependent noise dataset from the oil rig. Section 4 performs the evaluation of some commonly used neural networks and comparisons to the selected ELM-based learning. Section 5 concludes the paper.

2. Input and output variables selection

The neural networks determine the relationship between the thirteen input variables to the four output targets namely: spatial sound pressure level (SPL), spatial average SPL, structure-borne noise and airborne noise at different octave frequencies (e.g. 125 Hz to 8000 Hz). The spatial SPL consists of both direct and diffuse field (or reverberant field) obtained from a commercial SEA modeling software called VA-One™ and MATLAB™, respectively. The spatial SPL is achieved from the logarithmic sum of both the direct field ($L_{p,dir}$) and reverberant ($L_{p,rev}$) component as shown.

$$L_{p,spatial} = 10\log(10^{0.1L_{p,dir}} + 10^{0.1L_{p,rev}}) \tag{1}$$

The VA-One™ software is also capable of computing both the airborne and structure-borne noise from (Ji and Chin, 2015; Azma et al., 2013) but at the expense of high computational time and resources. The input variable for AOS-ELM training are selected based on two broad principles: (a) variables that describe the acoustics and structure features of the offshore platform, and (b) variables that influence the response of the sound fields. However, the input variables require a prior understanding of the acoustic problem on the board of the jack-up rig at a different frequency. Also, the acoustic environment on the jack-up rig is quite complex due to its large number of noise and vibration sources located within a compact space. The use of wide variety of different materials for room construction complicates the acoustics room modeling.

The airborne noise governs the compartment's sound field where the machinery is situated. In general, the SPL measured in the airborne-dominated compartments can be approximated by the Heerema and Hodgson empirical formula (Heerema and Hodgson, 1999). The formula depends on the room geometry, source power level, source–receiver distance, absorption coefficient, and fitting density of the source room. Unfortunately, the airborne noise in the source room can penetrate through the common bulkheads or decks to influence the noise in the adjacent rooms. The transmitted acoustic energy depends on the incident acoustic energy and transmission loss which is determined by the plate material properties and thickness as shown.

$$L_{adj} = L_{source} - R + 10\log\frac{S}{S\alpha} \tag{2}$$

where L_{adj} and L_{source} are the SPL of the adjacent room and source room, respectively. The transmission loss and surface area of the common bulkhead are R and S, respectively. Here α is the mean absorption coefficient of the adjacent room. In some cases where the SPL within the source and the adjacent room are not known, the range of SPL is provided by the regulation namely NORSOK S-002 for eight different room types based on the permitted noise levels on the board of the offshore platform as shown below.

- Type 1- unmanned machinery room (maximum allowable 110 dBA)
- Type 2- unmanned machinery room (maximum allowable 90 dBA)
- Type 3- manned machinery room (maximum allowable 85 dBA)
- Type 4- unmanned instrument room (maximum allowable 75 dBA)
- Type 5- store, workshop and instrument room (maximum allowable 70 dBA)
- Type 6- living quarter public area, change room, corridor and toilets (maximum allowable 65 dBA)
- Type 7- living quarter public area, laboratory, local control room, galley, mess room, office, gymnasium, lobby (maximum allowable 60 dBA)
- Type 8- cabin, hospital, central control room (maximum allowable 45 dBA)

On the other hand, the structure-borne sound is directly caused by vibrating machinery induced mechanical force, or indirectly by the structure excitation due to incident airborne noise. The energy radiated by structures are proportional to the plate's radiation efficiency, surface area, density, sound propagation speed, and the square of plate vibration