


Chapter 6

Modelling of Engineering Systems With Small Data: A Comparative Study

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ABSTRACT

This chapter equitably compares five different artificial intelligence (AI) models and a linear model to tackle two real-world engineering data-driven modelling problems with small number of experimental data samples, one with sparse and one with dense data. The models of both cases are shown to be highly nonlinear. In the case with available dense data, multi-layer perceptron (MLP) evidently outperforms other AI models and challenges the claims in the literature about superiority of fully connected cascade (FCC). However, the results of the problem with sparse data shows superiority of FCC, closely followed by MLP and neuro-fuzzy network.

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INTRODUCTION

Nowadays, engineering world witnesses two partly conflicting realities:

1. Model-based design/optimisation/control are on rise (Madni & Sievers, 2018; Pal et al., 2022), and analytical and numerical models of many engineering systems cannot serve their purpose satisfactorily, e.g. as detailed in (Li et al., 2022; Mohammadzaheri et al., 2012a; Mohammadzaheri et al., 2020; Rahbar et al., 2022). This leads to an ascending demand for data-driven models, developed with experimental data.
2. Experiments take time and cost. Hence, experimental data sets often consist of limited number of samples, or they are small.

That is, engineers are more likely to deal with small data rather than big data (Mohammadzaheri et al., 2018a). Thus, developing accurate models out of small data is a crucial task for engineers (Chang et al., 2015; Zhang et al., 2022). There are a lot of piecemeal research in the literature reporting development of data-driven models for engineering systems with small data, e.g. (Kokol et al., 2022; Liu et al., 2023; Taajobian et al., 2018). However, no comparative research was found on modelling of engineering systems with small data, though a few were found in other areas (Collins et al., 2017; Steyerberg et al., 2000), as the value of models developed with small data is not limited to engineering (Goel et al., 2023; Kitchin & Lauriault, 2015).

AI provides powerful tools to model intricate engineering systems with their input-output data (Castro, 2018; Garg et al., 2015; Li et al., 2022). The research question is which AI method suits best to data-driven modelling of engineering systems, when only a small set of data is available. The answer to this question, which necessitates an unprecedented even-handedly comparison of the AI techniques for data-driven modelling of engineering system with small data, is the main contribution of this chapter. In order to answer the aforementioned research question, several AI-based data-driven models were developed with small data to solve two real-world engineering problems: (i) head estimation of an electrical submersible pump (ESP) lifting two-phase petroleum fluids, detailed in (Mohammadzaheri & Ghodsi, 2018) and (ii) selection of the sensing resistor in a charge estimator of a piezoelectric actuator, detailed in (Mohammadzaheri et al., 2019). Neuro-fuzzy and FCC networks, MLPs, and exact and efficient Radial Basis Function Network (RBFN) models as well as linear models have been developed to tackle problems (i) and (ii).

PROBLEM STATEMENT

This section briefly explains dual engineering problems, mentioned in the introduction, which were solved in this research using AI data-driven modelling techniques. The AI techniques will be compared based on their performance in solving these problems:

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