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STEPS TOWARDS A SELF CALIBRATING, LOW REFLECTION NUMERICAL WAVE MAKER USING NARX NEURAL NETWORKS

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Abstract. Numerical wave-makers are important for accurate simulations of marine two-phase flows. One important aspect of the suitability is the ability to recreate a given surface elevation time trace at a given location in the tank. This paper presents first applications of NARX neural network techniques for the calibration of wave tanks. Preliminary results indicate good results can be achieved even for highly non-linear waves.

1 INTRODUCTION

The accurate application of computational fluid dynamics methods to problems in marine and offshore engineering depend largely on the ability to create accurate representations of gravity water waves in the computational domain. Many different methods have been proposed to create and absorb waves in simulations, but as in experimental test facilities, it can still be difficult to create an exact target time trace of surface elevation at a certain position [6]. Most experimental facilities rely on tank transfer functions, which describe the relation between the wave amplitude and the wave maker input for each frequency component used to generate a time series [5]. By decomposing a surface elevation trace, the phase lag and amplitude of each individual component can be obtained and a wave trace can be created. This method is of course limited to a flat bottom and cannot take into account non-linear interaction between waves. In addition, numerical tools are also often used to simulate only very short time traces, methods based on spectral separation of individual components might not be readily applicable.

Neural networks, a type of machine learning tool based to some extend on biological examples, have been shown to work well in many cases where complex non-linear

interactions are of interest and sufficient training data is available [1]. Applications in coastal engineering have ranged from the prediction of ocean wave parameters to tidal levels, damages of coastal structures, the prediction of seabed liquefaction, changes of the near-shore morphology and the prediction of wave heights and periods [3, 4].

Only one application of neural networks to the calibration of an experimental wave maker is known to the author [2]. Neural networks were used to predict the amplitude for regular waves and the wave energy within specific wave period bins for irregular waves. However, this work did not consider calibration of a given surface elevation trace.

2 APPLICATION TO A WAVEMAKER

The numerical wave tank used in this paper is based on the momentum source wave maker presented in [6]. The domain is 13.4m long and 1m high. The water level is 0.338m. Dissipation zones stretch about three meters at both ends of the tank. The wave maker zone is located 4.1-4.6m from the left and reaches from the bottom to the water surface. The wave probe at the calibration position is located at x=8.487m.

A nonlinear autoregressive exogenous model (NARX) neural network is used to find the wavemaker input that creates a target surface elevation. NARX neural networks belong to the recurrent neural network types, which means that the predicted value of the output is also used as an input in the network. Those types of networks have been developed specifically for the simulation of time dependent, multiple input prediction problems. Besides the number of hidden layers the lag between the recurrent input and the number of exogenous inputs to be used must be chosen. All simulations presented in this paper used the following algorithm:

- The feedback delay was chosen based on the lag of significant autocorrelation of the output signal
- The input delay was chosen from the lag of the significant cross correlation of the input and output signal
- The number of hidden layers was then determined by increasing the number of layers, if no more improvement in training results was seen, the last number of layers was used

The calibration process for a desired surface elevation begins with running a random input to the wave maker for 30 seconds. The obtained surface elevation is then used with the known wave maker input to predict a suitable wave maker input for the next simulation. The simulations are always started at each run from still water condition. It would be expected that with a larger number of training data each successive run produces better results. As an error measure the mean square error (MSE) and the mean square relative error (MSRE) are used in this paper.

3 DELAYS

[1] has described some issues with long-term memory of Neural Networks and some improvement NARX methods offer. Tests revealed that the networks had significant problems modelling the relationship between wave maker input and surface elevation. It was found that shifting the surface elevation by approximately the time the wave needed to travel across the tank significantly improved the predictions.

Figure 1 presents the development of MSE and MSRE over successive simulations. It would be expected, that each run reduces the error since more training data becomes available. A simulation without any delay, that is feeding the wave maker input and surface elevation directly into the simulation, yields very bad results. MSE and MSRE stay almost constant or even increase with more available data. Increasing the delay to 2 seconds results in even 2 or 1.3 times larger MSE or MSRE respectively. The errors can be seen to decrease significantly for a delay of 3 seconds. MSE and MSRE now also show a decrease over the number of runs. Figure 2 shows the target surface elevation time trace and the result achieved after 40 runs. For the most part, between 2 and 8 seconds, the agreement is remarkable. It should also be noted, that the waves used in this example are quite extreme, with a wave height of about half the water-depth.

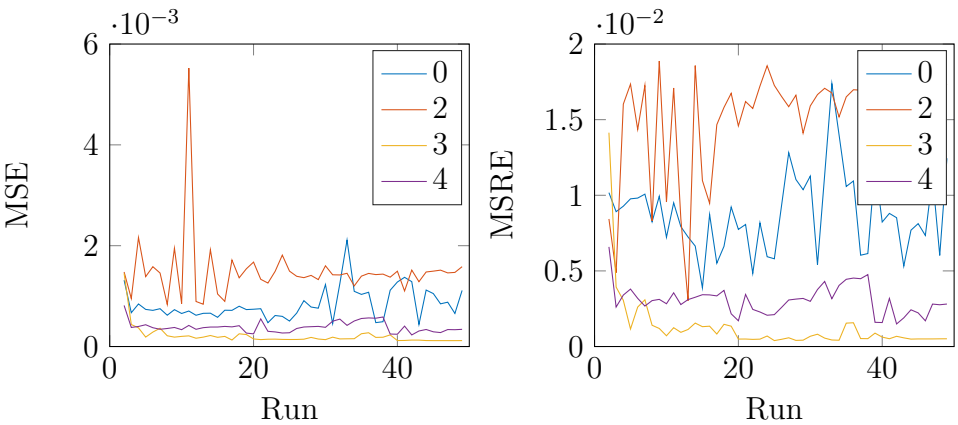

Figure 1: Comparison of MSE and MSRE over runs for varying delay times.

4 RESTART AS INPUT

Although these first results are encouraging, restarting each iteration from still water might cause issues. A restart is required to accommodate the delay feature described above, but it seems plausible that better results could be obtained if the information about restarts was used in the learning process. The network was thus extended to two inputs. One is as before the surface elevation, but now a second auxiliary variable is used to indicate the beginning of a new run. A comparison of the errors and actual results of surface elevation are shown in figures 3 and 4. It can be observed that the two input

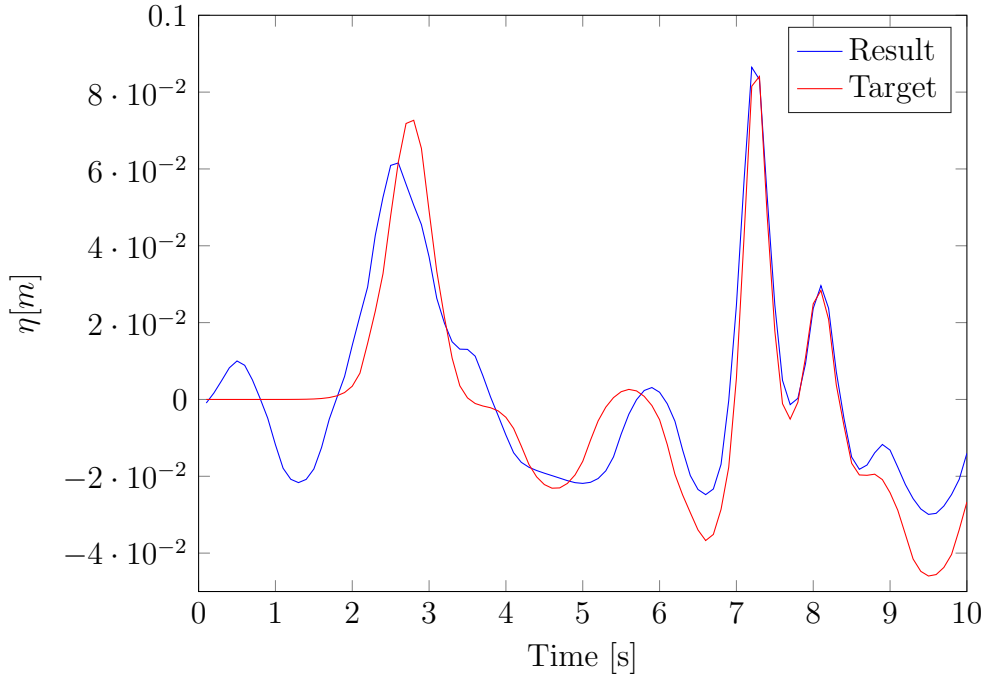

Figure 2: Target and achieved surface elevation trace after 49 runs.

version, that is the neural network with knowledge of the restart, show no improvement during the first 20 runs. This might be attributed to the lack of actual training data for the restart variable during the first runs. Between 30 and 40 runs the results are somewhat better than the previous version. Interestingly, for more than 40 runs, the absolute and the relative mean square error increase again and remain higher for the two input version. This result requires further investigation.

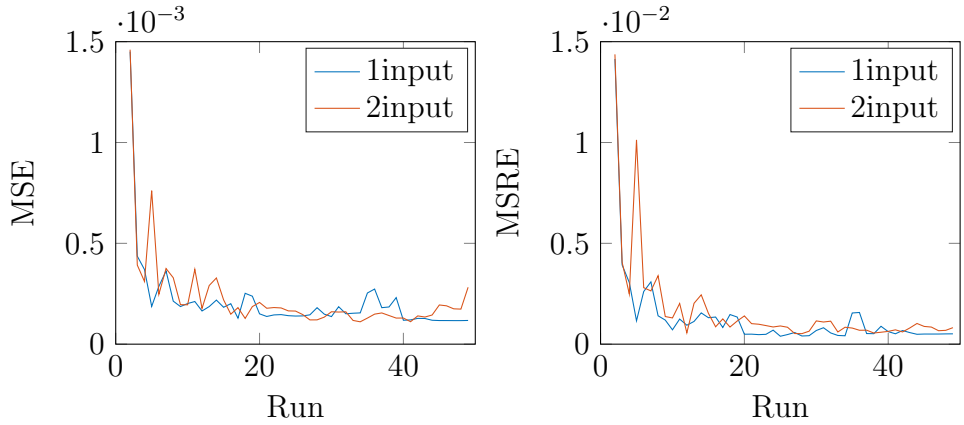

Figure 3: Comparison of MSE and MSRE over runs for single and two-input runs.

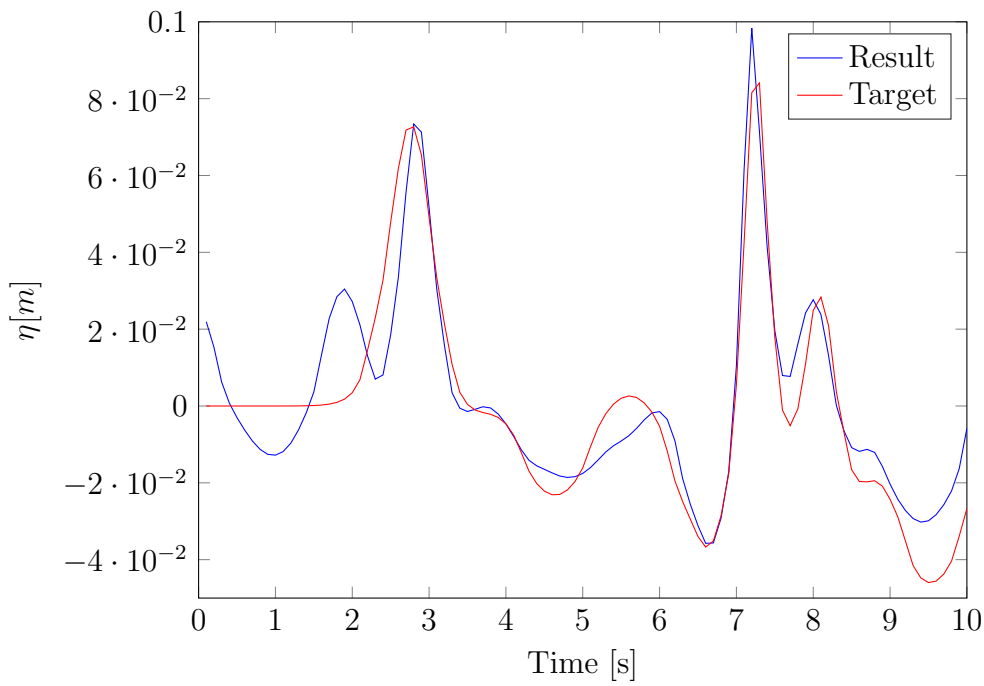

Figure 4: Target and achieved surface elevation trace after 40 runs for the 1 and 2 Input set-up.

5 CONCLUSIONS

With a relative mean square error of less than 0.5% after only a few iterations NARX neural networks have demonstrated to be a valuable tool for the calibration of time traces in wave tanks. It is believed that further investigations, especially in the optimal choice of feedback and input delays and number of hidden layers will further improve results.

6 ACKNOWLEDGEMENTS

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