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Machine learning for early stage piping design

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By Ilker Telci

The design and construction of pipeline systems consist of several steps beginning from before Front-End Engineering Design (Pre-FEED) to Engineering-Procurement-Construction (EPC). Pre-FEED and FEED stages involve the initial conception and feasibility assessment of the systems. Their detailed design is finalized in the EPC stage of a project. In the early stages (e.g. Pre-FEED) of a project the main concern is the estimation of the project cost. These design stages have high impact on the sustainability, performance, and the cost of the final product[1]. Although the design is at a conceptual level at this stage, an accurate cost estimate is crucial for the success of the overall project. The cost of piping systems mainly depends on the pipe class (pressure capacity) to be used and the piping supports. The decision on the pipe class requires information on the expected maximum pressure in the pipe segments; the support capacity can be determined based on the expected maximum dynamic load the pipes may encounter.

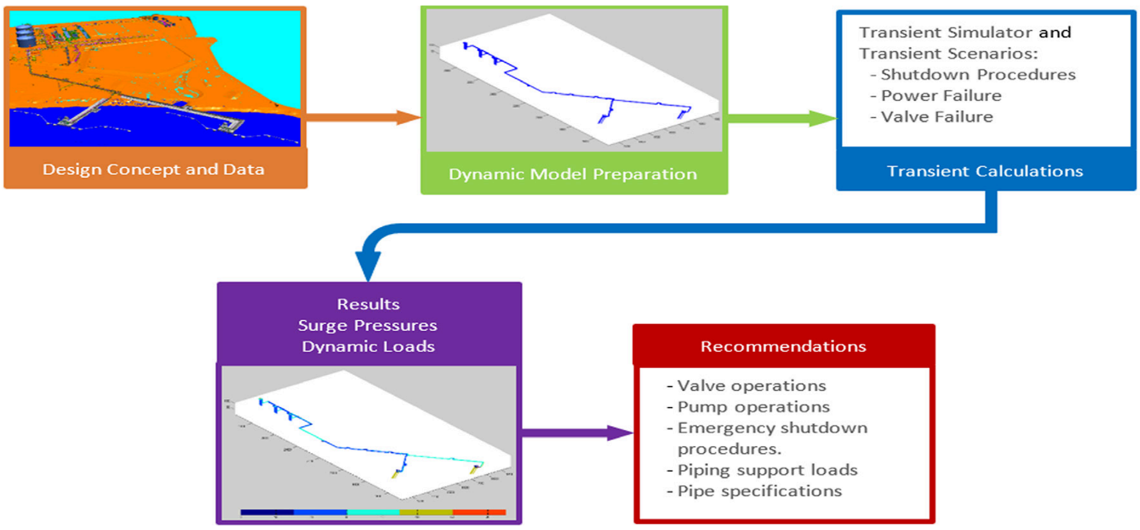

Figure 1 | Typical work process of a hydraulic transient analysis.

If a system is subject to hydraulic transients, or water hammer, the design pressures and forces acting on the pipes are mostly governed by these events. For more information on hydraulic transients, readers are referred to the issue number 2/2020 of the Hydrolink Magazine[2]. Hydraulic transient (water hammer) analysis is the primary method for estimation of the surge pressures and dynamic loads in pipeline systems. The primary outcomes of a hydraulic transient analysis are the estimation of maximum surge pressures and dynamic loads acting on the pipe segments as a result of various operation or accident scenarios such as emergency shutdowns, power failures, and valve failures (i.e. closures). Operational or design related recommendations to mitigate excessive surge pressures or dynamic loads are also provided as a result of the transient analysis. A high-level schematic description of the work process in a typical transient analysis is provided in Figure 1.

Transient analysis requires a detailed model of the system including liquid and pipe properties (e.g. liquid density, vapor pressure, modulus of elasticity of the pipe material), pipe sizes (diameters, wall thicknesses and lengths), elevations, hydraulic characteristics of pumps and valves, and operational procedures of the pipeline system (e.g. emergency shutdown procedures). It is not possible to obtain all these required data at the conceptual design phase of the project. Thus, several assumptions are required for the missing data in order to complete the transient model used to estimate surge pressures and dynamic loads in the system. Every assumption adds some uncertainty to the modeling results. Also, transient processes which result from sudden stoppage of the flow due to valve closures or liquid column separation and rejoining have highly nonlinear and counterintuitive dynamics. Therefore, constructing a detailed hydraulic transient model is not justified at the early stages of a project.

One alternative way of making an informed engineering judgement on the transient response of a system at an early design stage can be reviewing the results of past transient analyses performed as part of the detailed design of similar systems. For this purpose, a database of similar systems was prepared. The database includes the list of pipes with relevant parameters such as pipe size, length, elevation, region, and associated transient analysis results (i.e. maximum simulated surge pressure and dynamic load). This type of database is a useful asset for hydraulic engineers by providing them with statistical information on not only the typical parameters of the piping systems, but also with the estimated transient responses. The hydraulic engineers utilizing the database should be aware of critical background information on the hydraulic system design of each of the projects included in the database. For example, outliers with respect to parameters such as fluid properties, valve closure times or pump moment of inertias should be noted.

Machine Learning (ML) methods can be used to analyze the available data and develop a mathematical model to make predictions on the surge pressures and dynamic loads in a similar system. Artificial Neural Networks (ANN) was chosen as the machine learning method and the database was used to train an ANN to make predictions on the surge pressures and dynamic loads that may occur on a pipe with a given set of parameters.

Artificial neural network applications in hydraulics and hydrology

ANNs are powerful tools that can be used to identify relationships from given patterns. Large scale complex problems such as pattern recognition, nonlinear modeling, classification, association, and control can be solved using ANNs [3]. ANNs have many applications in the fields of hydraulics and hydrology. Several examples of hydrological applications of ANNs such as rainfall-runoff modeling, stream flow modeling, water quality modeling and precipitation estimation can be found in the literature [4]. Some hydraulic applications of ANNs in pipeline systems include monitoring and detecting leakage points in pipelines [5] and predicting internal corrosion in the pipelines [6,7]. ANNs ha ve also been suggested as design aids for air vessels in transient protection of pipe networks [8]. Recent research focuses on more advanced machine learning methods for the solutions of partial differential equations such as the Burgers' equation, Darcy Flow and Navier-Stokes Equation [9].

Liquefied Natural Gas (LNG) loading systems

LNG loading systems were selected for the pilot application of ANNs in the prediction of surge pressures and dynamic loads. This choice was made to address the need of the engineers working on these projects who frequently require early stage design evaluations for these pipe systems.

LNG is the liquefied form of natural gas, a mixture of hydrocarbons, which is usually transported and stored at a temperature very close to its boiling point at atmospheric pressure (approximately -160 °C). Since LNG is a cryogenic substance, physical contact or spillage may result in personnel or equipment hazard [10].

Figure 2 | Example LNG loaFigureding system.

Specially designed loading systems are used to transfer LNG from the storage tanks of a terminal to ship vessels that transport the LNG to different destinations (Figure 2). Main components of these systems are the LNG storage tanks, the pumps, the LNG transfer lines and the loading berths, each equipped with loading arms. Loading systems can have single or multiple lines of these components depending on the design loading rate and shoreline conditions. Typical design flowrates are of the order of 12,000 m^3/h. LNG companies are looking for means of increasing the loading rate as much as possible to minimize the time required to fill up the tanks on the ship vessels. In a typical LNG loading system, the flow rate is maintained by the flow control valves located at the tank top on the discharge pipe of each pump. Shoreline, loading arm and Emergency Release System (ERS) valves are used during emergency shutdowns. Major components of a typical LNG loading system are shown in Figure 3.

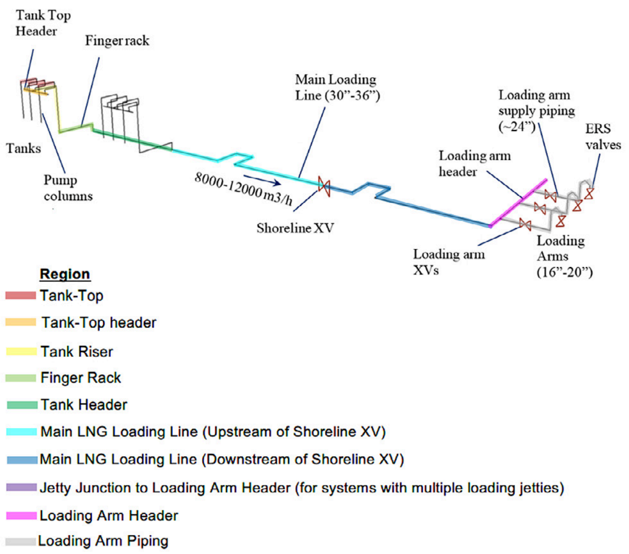

Figure 3 | Piping layout of a typical LNG loading system, showing the ten regions used for the training of separate ANNs.

The transient events which may cause pressure surges in LNG loading systems are planned and unplanned pump shutdowns, valve closures and emergency shutdowns. The system response to these transient events differs from region to region of the system. For example, a pump trip scenario is expected to have the highest impact at the tank-top piping when the pump discharge check valve slams, or when liquid column separation and rejoining occurs. An emergency shutdown scenario is expected to have the highest impact at the loading arms due to the closure of the Emergency Release System (ERS) valves and the Loading Arm emergency shutdown valves. A scenario with an unplanned closure (failure) of a shoreline emergency shutdown valve may impact the piping in the viscinity with a completely different hydraulic transient mechanism at the upstream and downstream sides of the valve (i.e. pressure increase on the upsream side, and pressure decrease with possible liquid column separation and rejoining on the downstream side). These observations are the primary reason for the decision to develop separate ANNs for different regions of the LNG loading system.

Transient analysis of the LNG loading systems involve simulation of a large number of scenarios and determining the maximum estimated surge pressures and dynamic loads on each pipe segment. If the estimated surge pressures or dynamic loads are excessive, various mitigation options are investigated. Since LNG is a hazardous material surge mitigation options which may cause spillage of LNG, such as air inlet valves are not acceptable. Typical mitigation options are slowing down valve closures and adjusting valve closure and pump trip timings. In some cases, surge vessels can be used as a mitigation option. The mitigation options applied in the previous projects are important parameters to be considered in determining the ANN's training database.

Hydraulic transient database for LNG loading systems

A hydraulic transient simulation requires a wide range of detailed system information such as fluid properties, pipe properties (e.g. sizes, length, elevations) pump characteristics, valve characteristics, flowrate, boundary conditions (e.g. tank liquid levels and ship manifold pressure), valve closure times, and pump trip times. All these are input parameters for a single transient scenario. A hydraulic transient analysis involves simulation of multiple scenarios with various valve/pump actions for a variety of initial conditions (e.g. flowrate) and boundary conditions. Therefore, the results of the transient analysis (i.e. estimated maximum surge pressures and dynamic loads) are a combination of multiple simulations. In the current approach, the purpose of developing ANNs is not to predict the results of any specific single transient scenario, but to predict results of an overall transient analysis.

When candidate parameters to be included in the database are considered, fluid properties and typical design flowrate (~12,000 m^3/h) are similar among different LNG loading systems. Typical valve and pump characteristics are similar too, and can be decided in the detailed engineering phase of the project (EPC). Typical valve and pump actions (timing and durations) are also similar for most LNG loading systems with possible adustments during EPC. As a result, in the current approach, most of the parameters used in the hydraulic transient simulations may not be needed as input parameters for the ANN development. When selecting the parameters of the hydraulic transient database, the main driver is the data availaibity during early design stage. Therefore, only simple parameters such as pipe segment length, pipe diameter, relative elevation of the pipe with respect to the pump centerline, and relative location with respect to the check valve were selected for the ANN application.

In the current study, a database of pipe segments was prepared from three previously analyzed LNG loading systems including the above mentioned parameters along with the respective transient analysis results (estimated maximum surge pressures and dynamic loads). Two of these systems were selected as the training dataset for ANN development and the third one was spared as the test set. In the future, the author intents to increase the number of systems used for the training of the ANNs, which is expected to improve their predictive performance.

Developing and training ANNs for LNG loading system transients

ANNs are highly flexible tools for identifying relationships from given patterns. Users can define many different ways of training an ANN for a given problem. For the LNG loading system example, Neural Designer[11], a machine learning platform to build, train, and deploy neural network models, was used. Due to the disctinct hydraulic transient responses of different regions (parts) of the LNG loading system, it was decided to train ANNs separately for each region. These regions were selected based on their relative locations with respect to the pumps, tanks and main valves. Ten separate ANNs were trained for ten selected regions across the loading system as indicated in Figure 3. Figure 4 provides general views of tank, loading line and jetty area.from different loading systems As a result, each ANN was developed to have different input parameter requirements. For example, while the ANNs for the tank top header, tank riser, finger rack and loading arm piping have the pipe segment length as the only input parameter, the tank top piping from the individual pump to the tank top header requires input related to the relative location of the pipe segment with respect to the check valve (VC1), and the main LNG loading line requires as input the diameter and relative elevation of the pipe segment with respect to the pump center line in addition to the pipe segment length (Zr). These input parameters were determined by analyzing the sensitivity of the transient outputs (surge pressures and dynamic loads) to the individual input parameters. Three example architectures are provided in Figure 5 for the ANNs developed for the tank top piping, tank riser and main loading line upstream of the shoreline valve. In this figure, the yellow circles represent scaling neurons, the blue circles perceptron neurons, the red circles unscaling neurons, and the purple circles bounding neurons. In the layer of scaling neurons the maximum and minimum scaling method is used, which produces a data

Figure 4 | General view of LNG loading systems. (A) Storage tanks area, (B) Main Loading Lines, (C) Jetty Piping.

set scaled between -1 and 1. In the layer of unscaling, scaled outputs from the neural network are converted back to the original units. The bounding layer limits the outputs of the unscaling layer between the predefined boundary values (in this case, the highest and lowest estimated maximum surge pressure and dynamic load in a given region). More information can be found in the Neural Designer Tutorial[12]. The hydraulic transient data from two previously analyzed loading systems were used as the training set.

Testing ANNs for LNG loading system transients

The transient analysis of a third LNG Loading System was used for testing the performance of the ANNs. Since the transient parameters and transient results of this loading system were not included in the training set, the predictions of the ANNs were deemed to be a good representation of their performance. One example comparison between the ANN predictions and transient analysis re sults for the test case is provided in Figure 6 for the main LNG loading line downstream of the shoreline valve indicated with the blue line in Figure 2. If the ANN performance is defined as how closely the transient analysis results are predicted by the ANN, the results in Figure 6 is one of the best among the ANNs built for different regions. As can be seen in Figure 6, the error in the predicted pressures by the ANN is less than 3 percent, with the exception of one segment where the error is 7.5. The error in the predicted forces is less than 30 percent, with the exception of one segment where it is 80 percent. When overall results are considered, it can be said that the surge pressure predictions made by the ANNs are slightly conservative compared to the transient analysis results. However, this overprediction would not result in a higher-class piping in the early stage design decision. When the dynamic load predictions are analyzed, ANN predictions are significantly higher than the transient analysis results for some segments. This observation warrants further studies and improvements in the ANNs developed for the LNG loading system transients. When evaluating the ANN performance test results, it should be considered that in the proposed approach, the results of a highly complex numerical process is being predicted by the ANN with limited input parameters. The actual physical processes such as liquid column separation and rejoinings, pressure wave reflections at the dead-end pipings, and supepositions estimated in numerical models of the trainin g dataset may not be similar with those in the test data set.

Limitations

The main limitation in training the ANNs was the number of available data due to the limited number of transient analyses included in the data set. This limitation will be overcome by including more and more LNG loading system transient analyses to the training data set. Similarly, the test cases were limited. As the number of training and test data increases, the perfor-mance of the ANNs will be assessed more accurately using statistical indicators such as root mean square error.

Recommendations

ANNs can provide valuable information for cost estimation purposes during the very early stages of pipe system projects. In using ANNs, the hydraulic specialist should be aware of all hydraulic components of the systems (e.g. valve closure times and surge mitigations) when preparing the training and test data sets. However, the hydraulic specialist should always keep in mind that the ANN predictions are not confirmed transient analysis results, but they can provide valuable supplemental information for early stage design decisions at a time when no hydraulic transient analysis is performed. ANNs are not intended to and will not replace hydraulic transient analysis for the final design of pipe systems.

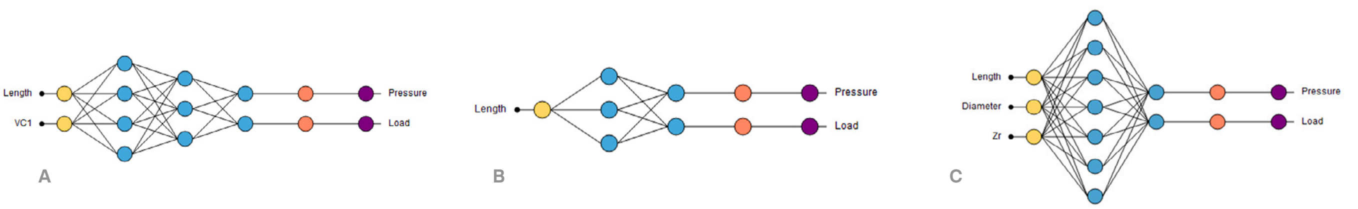

Figure 5 | ANN architectures for (A) tank-top-piping, (B) tank riser, (C) main loading line upstream of the shoreline valve.

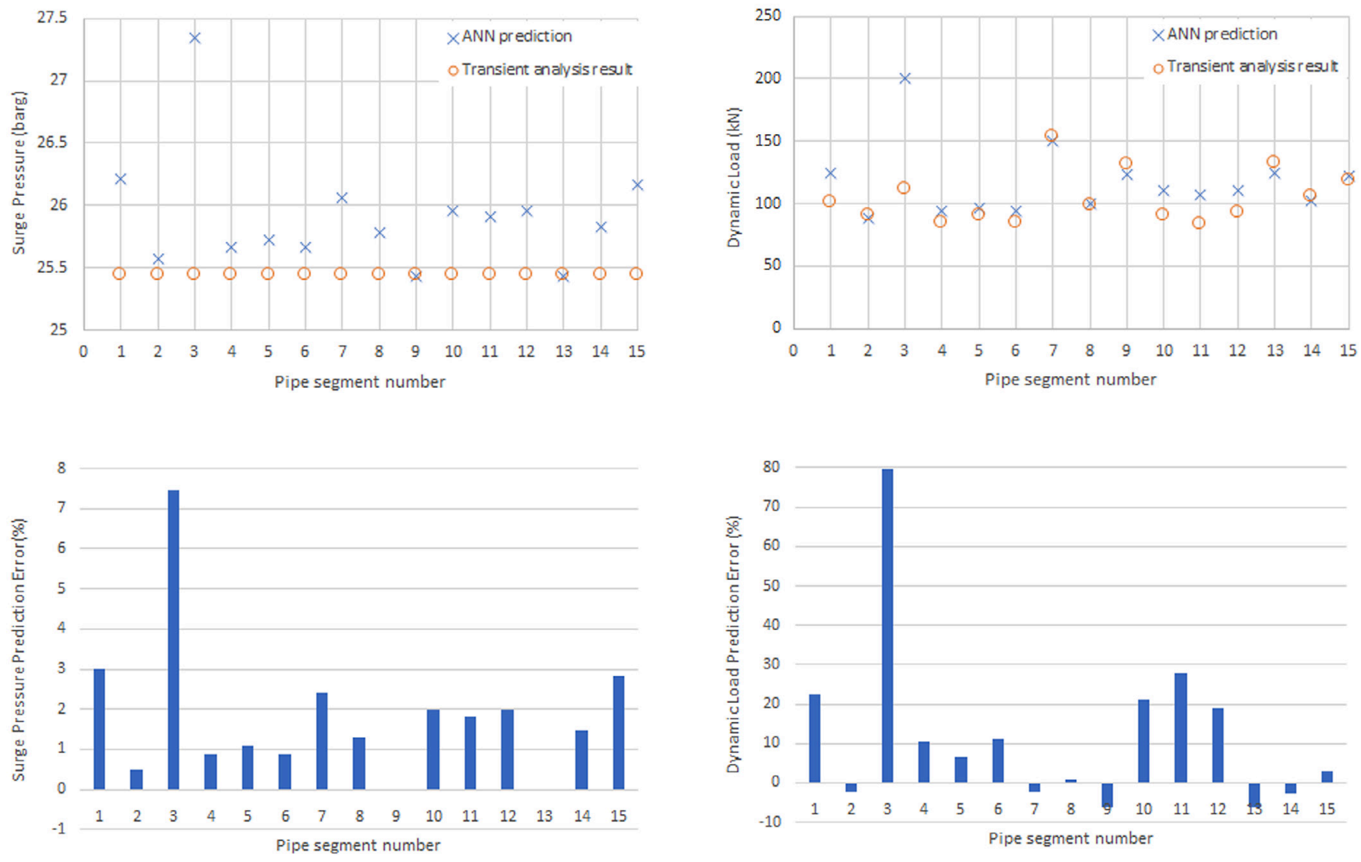

Figure 6 | Comparison of ANN predictions with the transient analysis result for the pipe segments in the main loading line downstream of the shoreline valve.

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