Digital twin of the Pirot water system for dynamic resilience assessment

Milan Stojković*, Dušan Marjanović*, Luka Stojadinović*, Nikola Milivojević*

* Jaroslav Černi Water Institute, Belgrede, Serbia
milan.stojkovic@jcerni.rs, dusan.marjanovic@jcerni.rs, luka.stojadinovic@jcerni.rs, nikola.milivojevic@jcerni.rs

***Abstract*—This research aims to propose a novel framework for the assessment of the consequences of hazardous events on a water resources system using dynamic resilience. The two main types of hazardous events considered are: a severe flood event, and an earthquake. Given that one or both hazards occur, this framework utilizes a digital twin based on a system dynamics (SD) model, backed by an Artificial Neural Network (ANN) to estimate the dynamic resilience. The ANN was trained using a large, simulated dataset ranging from very mild to extreme hazard combinations. The ANN's efficacy was quantified using the average relative error metric which equals 2.14% and 1.77% for robustness and rapidity, respectively.**

I. INTRODUCTION

A general increase in available data and computing capacity attracts large interest in digital twins, especially in the water resources sector [1]. The term "digital twin" refers to a digital replica of a physical system providing a digital representation of a specific part of the water system (e.g. water facilities, hydropower plant, spillways). It uses real-time measure data to simulate expected or critical physical water system behavior beyond the design water system envelope.

Our research utilizes a digital representation of the Pirot water system, based on a chain of models, to assess the dynamic resilience during hazardous events. The chain of models consists of the hydrograph model describing the flood dynamics over the simulation time, earthquake failure model to simulate the impact of earthquakes on the element of the system reservoir and system dynamics (SD) simulation model to mimic the non-linear behavior of the reservoir system.

Then, the dynamic resilience model is used to estimate the risk of the water system related to flood events with varying return periods followed by a decreased capacity of water system elements brought about by earthquakes. Finally, an artificial neural network (ANN) is employed to determine the related risks enabling a real-life application at the decision-making scale.

II. RESEARCH QUESTION

The hydrograph model generates a flood hydrograph that is used as an input into the SD model. Flood hydrograph generation consists of three steps; First, a flood magnitude (expressed as a return period) is generated from existing hydrological data. Secondly, a theoretical flood hydrograph shape is approximated by the Gumbel distribution. Finally, using the flood magnitude and shape of the flood hydrograph, flood hydrographs are generated using MC simulations with predefined upper and lower bounds.

The earthquake failure model generates varying earthquake events in order to thoroughly assess adverse effects on the reservoir system. The model itself is used to determine the dependence between the magnitude of the earthquake and the functionality of the system, as expressed by a functionality indicator (α), which describes a physical drop and corresponding effects in the system operation.

Furthermore, the model is constructed in such a way that the start time of the earthquake event corresponds with the flood hydrograph occurrence [2]. The SD model with a causal loop is developed to mimic the behavior of the water resources system. This SD model is the digital twin of the Pirot water system. It is characterized by the following blocks [3]: stocks, flows, and connectors.

The causalloops within incorporated into the digital twin provide a link between the system characteristics, inputs, and operational rules separately defined for flood protection facilities. Furthermore, the digital twin incorporates an additional model structure defined as functional indicators, given the fact that they implicitly describe the reduced capacity of the water system elements caused by natural or man-made hazardous events [3]. The digital twin mimics a multipurpose water resources system with a focus on flood management reservoir roles.

Additional water management roles are also incorporated within the digital twin allowing for the control of the discharge to suit the demand for hydropower generation, ecological flow improvements during low-flow periods, and losses from the water resources system. The digital twin takes as inputs the flood hydrographs, total releases from the water system, the functionality indicator of the spillway, and losses. Considering those inputs, its output is defined as water level in the system over the simulation time [4].

The dynamic resilience model is utilized in order to capture several significant numerical characteristics during a disruptive event that poses a serious threat to the water resources system and its belonging elements. The most of important of those characteristics are robustness and rapidity. Robustness represents the systems ability to resist disturbance, where rapidity is the systems ability to return to a pre-disturbance level of functionality.

Once a water system is unable to provide the required services under a hazardous event, its dynamic resilience starts to decrease, the minimal value to which the dynamic resilience of a system drops represents the systems' robustness. Upon the conclusion of a hazardous event, its dynamic resilience begins to increase, a system with a higher adaptive capacity will take less time to return to its pre disturbance state of functionality. This adaptive capacity is represented through rapidity, which is measured from the initial drop in dynamic resilience to a complete return in functionality.

Using a randomly generated set of hazardous events with different impacts on the element system, an ANN is employed to extract the information about the flood dynamic resilience of the system. Accounting for the fact that the flood dynamic resilience depends on hazards with variable magnitude, time of occurrence, and duration, there is a need to generalize the assessment of dynamic resilience using an ANN. The biggest advantage of the NARX ANN is its ability to provide the information on the dynamic resilience of a system in a timely manner, enabling the prediction needed to perform adequate strategies aimed at reducing the adverse effects of the hazardous events.

The utilized NARX ANN architecture has its advantages in its ability to account for the temporality of hazardous events, thus giving a more accurate representation of the dynamic resilience of a system following hazardous events. The ANN takes the maximum value of the flood hydrograph, the functionality indicator (which represents the earthquake) and the initial water state in the reservoir as inputs and attempts to reconstruct the robustness and rapidity of the water resources system. The optimization algorithm used is Levenberg-Marquardt, along with the sigmoid activation function.

III. RESULTS

The digital twin of the Pirot water resources system was implemented on an hourly basis, using system dynamics software (Vensim), to provide an adequate response to dynamic hazardous events.

The data used for ANN training encompasses 1000 independent simulations of coinciding hazardous events with low joint probability distributions, as well as the system response to those hazardous events. The choice of 1000 simulations was influenced by the need to cover a large span of hazard magnitudes. Please bear in mind that the simulations where potential hazards do not cause significant flood-related risks were excluded upon generation from the dataset and that the entirety of the generated dataset contains values with flood dynamic resilience lower than 1.

From the 1000 simulations, the most extreme hazard combination consists of a hydrograph peak value of 3233 m^3/s, corresponding to a return period of 6183 years, with a significant earthquake magnitude. This combination corresponds to a flood dynamic resilience decrease to roughly zero (the minimum value of robustness equaling to 0.03 given in Fig. 1a).

As expected, considering the magnitude of this flood event, the water levels in the Zavoj reservoir and spillway outflows reached the highest possible values. During these extreme flood events, the bottom outflow facility also reaches the highest possible value of discharge. Please note that the total capacity of the bottom outflow (80 m^3/s) is substantially lower than the spillway capacity (1820 m^3/s). For this extreme case, to retrieve system

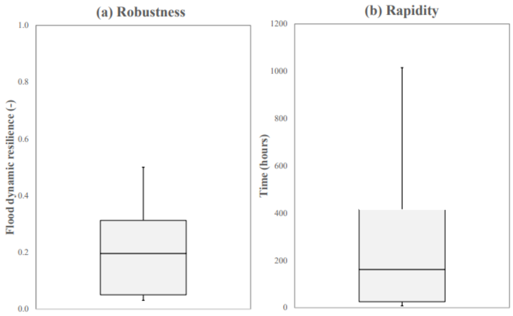

Figure 1. Flood dynamic resilience of the Pirot water resources system using the generated dataset of 1000 simulations: robustness (a) and rapidity (b)

functionality under such severe hazards the rapidity of the Pirot water resources system reached 1000 hours (Fig. 1b). In the case of moderate hazards, system robustness has a median of 0.2 (Fig. 1a), while the median rapidity was equal to 162 hours (Fig. 1b).

The ANN employed to model the dependencies between hazardous events with different impacts on the system elements and flood-risk metrics (robustness and rapidity) contains 3 hidden layers of 4 nodes each, and 2 output nodes.

The network is fully connected, and the hidden, as well as the output layers activation functions, were all sigmoid. The Levenberg Marquardt optimization algorithm consisted of 1000 epochs. The ANN's inputs were: (1) The maximum value of the generated flood hydrograph (Q_max), (2) the reduction of the functionality indicator (alfa min), and (3) the initial state in the Zavoj reservoir (V start).

The dataset was split into 3 subsets: the training set, validation set and test set using a 70%-15%-15% split, respectively. Furthermore, the network was trained 200 times and the best of those networks was selected to avoid the potential problem of a local minimum in the optimization which can adversely affect the network's further application.

The selection of the best network was based on the Root Mean Square Error (RMSE) metric. When selecting the best network, robustness and rapidity were valued with equal importance.

The metric used to quantify the efficacy of the ANN approximation was the relative error of the approximation. For robustness, that relative error was equal to 2.14%, whereas for rapidity that relative error was equal to 1.77%. Moreover, the RMSE values for robustness and rapidity were equal to 0.004 (-) and 12.7 hours, respectively. While the RMSE for rapidity may seem significant, considering the timespan in which rapidity fluctuates (Fig. 1b), such an error is not substantial.

Comparing the ANN approximations with simulated values for the same input parameters, it is of note that robustness and rapidity diverge from the corresponding observed parameters for higher values of flood dynamic resilience-related parameters. These diverging extreme values are to be expected given the sigmoid activation function which may not catch the extremely high values of flood dynamic resilience-related parameters. However, these results indicate that that ANNs are capable of adequately approximating the wide range of robustness and rapidity values needed for real-time operations of the Pirot water resources system.

IV. Conclusion

Using a digital twin to simulate the behavior of the Pirot water resources system enables the simulation of a system response to generate hazardous events which may not occur. This approach also introduces an avenue which allows for the simulation of the difficulties introduced by the ever-increasing complexity of water resources system solutions and environmental issues. Considering an increase in the availability of hydroclimatic data, alongside an increase in computing power, machine learning algorithms have become a useful tool for flood risk and impact assessments. In this research, flood-related risk characteristics were captured by postprocessing a large amount of data, which was later utilized for the supervised training of an ANN. The results of the training suggest that it is possible to train a network to approximate the rapidity and robustness of a system. Especially in the case of rapidity, where the approximation highly matches the target values. While the real system is susceptible to measurement errors, the timescale of rapidity allows for such errors to occur without significantly affecting resilience predictions. The same cannot be said for robustness, which the network cannot capture as efficiently due to the rapid changes in flood dynamic resilience after a disturbance is introduces.

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