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ANALYSIS OF THE EXPANSION OF THE PANAMA CANAL USING SIMULATION MODELING AND ARTIFICIAL INTELLIGENCE

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ABSTRACT

This paper presents preliminary analysis of the Panama Canal Expansion from the viewpoint of salinity in the Gatun Lake and the utilization of neural networks. This analysis utilized simulation modeling and artificial intelligence. We have built several discrete and system dynamics simulation models of the current Panama Canal operations and the future expansion which have been validated with historical and projected data and Turing/expert validation by engineers of the Panama Canal Authority. The simulation models have been exercised in order to generate enough information about the future expansion. This information has been used to develop neural networks that have the capability to indicate the volume of the Gatun Lake and its respective salinity taking into consideration lockages, spillovers, hydropower generation, fresh water supply volumes, and environmental factors such as precipitation, tides, and evaporation. Support vector machines were used to build time series regression models of the evaporation of Gatun Lake.

1 INTRODUCTION

The Panama Canal is located at a strategic location at the narrowest point between the Pacific and the Atlantic Ocean. The canal is 48 miles long and connects both oceans saving an 8,000 miles trip (12,875 km) around the southern tip (Cape Horn) of South America. It is one of the greatest achievements for the global trade markets. The canal has contributed to the growth of trade between countries since it allows a shorter route, in terms of distance and time between countries and consumers. The Panama Canal has not only open opportunities for the great international markets but it also has help the progress of the region, since its vital for the commercial development of emerging Latin American markets. The Panama Canal currently carries 5 percent of world’s traded goods, and it is an important competitor in some very important shipping routes. For example, the Canal currently handles about 16% of the United States maritime trade, and more than 25% of the containerized trade between North East Asia and the East Coast of the United States (Alvarez et al. 2009). A global tendency of the maritime trade market is the raise on the oil prices, the Panama Canal represent a shorter itinerary for the ships.

Another important factor is that the world’s maritime ships have grown in quantity and capacity. The size of the ships has been growing as the demand of goods increases. The need of larger containers capacity supports a tendency of the use of larger ships. On the other hand, the 20th century Panama Canal model, with 49.7 miles in length, and 2 sets of locks on each side, carrying ships up and down 25 meters on a mountain range, is struggling to meet this demand. The 5.25 billion US dollar Panama Canal expansion project includes a new lane of traffic along the canal, with a construction of two locks complexes each of 426.72 meters long and 54.86 meters in width, one at each side of the canal, which means greater capacity and allows larger ships to transit (Panama Canal Authority 2006). The maximum size ship the canal can handle now is the Panamax (i.e., dimensions of 300 meters long and 30 meters across), but with the new expansion the PostPanamax ships (i.e., dimensions of 366 meters long and 49 meters across) will be able to transit (see Figure 1).

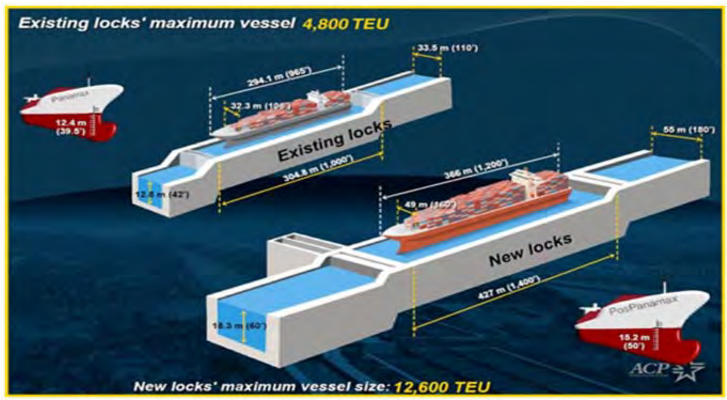

Figure 1: Comparison of the new and old locks sizes (adapted from http://www.oil-electric.com/2011/08/panama-canal-expansion.html).

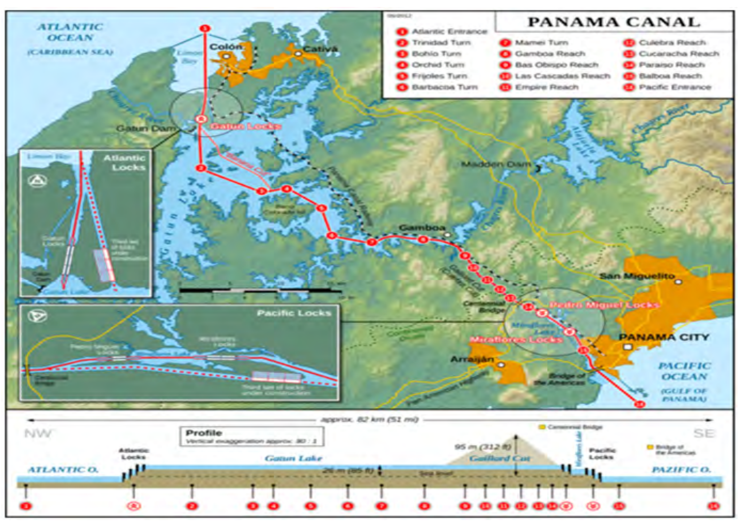

Figure 2: Points 2 (Atlantic side) and 6 (Pacific side) indicate the location of the new set of locks for Post–Panamax ships (adapted and modified from: http://en.wikipedia.org/wiki/File:Panama_Canal_Map_EN.png).

Gatun Lake is an artificial lake that was created when the Panama Canal was built in order to facilitate its creation (see Figure 2). The Gatun Lake has an area of 425 km^2 at its normal level and 26 meters above sea level. Gatun Lake not only provides the millions of gallons necessary to operate the Panama Canal locks when a ships pass through, but also provides drinking water for the cities of Panama City, Colon, and Chorrera (a city in the west of Panama City between the districts of Capira and Arraijan), which represents the region of greatest growth in Panama (Sandoval 2005). It is very important to emphasize that Gatun Lake constitutes the natural habitat for native Central American animal and plant species.

The Panama Canal expansion through a third set of locks presents new challenges. One challenge is the potential increase in the salinity of Gatun Lake above permissible levels. We have built several discrete and system dynamics models of the current Panama Canal operations and the future expansion. These simulation models have been validated with historical and projected data and Turing/expert validation by engineers of the Panama Canal Authority. These simulation models were also compared to other models developed by different organizations. Then, the simulation models have been exercised in order to generate enough information about the future expansion. This information is been analyzed by using techniques such as principal component analysis and neural networks. The neural networks have the capability to indicate the volume of Gatun Lake and its respective salinity taking into consideration the lockages, spillovers, hydropower generation, fresh water supply volumes, and environmental factors such as precipitation, tides, and evaporation. This decision tool can be used to plan certain aspects of the operations of the future and expanded Panama Canal.

2 SALINITY OF THE LAKES AND SYSTEM DYNAMICS MODEL

Salinity refers to the mass quantity of dissolved salts per unit of water mass or water volume (1 unit = 1 liter). Seawater's salinity (S) amounts to 35 parts per thousand (ppt). The chloridity (Cl), which is sometimes used, represents the mass quantity of chloride ions per unit of water mass or water volume. The Cl of fresh water should not exceed 0.2 to 0.25 ppt. This fresh water limit corresponds to a salinity value of 0.4 to 0.5 ppt.

The salinity diffusion was modeled using the exchange of mass transfer (Parchure et al. 2000; Marin et al. 2010). This involved the study of the different volumes and salinity gradients of the Panama Canal System: Water systems and Locks. In addition, it was complemented by collecting data using historical records provided by the Panama Canal Authority (and data collected by the research team).

Table 1: Physical dimensions of the Panama Canal (current).

Lock	Width (m) × Length (m)	Height over lock (m)	Depth under or over PLD (m)
L1	33.53 × 320.34	7.92	-15.85
L2	33.53 × 326.44	8.53	-6.20
L3	33.53 × 326.44	9.45	+3.44
L4	33.53 × 326.44	8.53	+3.96
L5	33.53 × 320.34	8.83	-4.67
L6	33.53 × 320.34	8.53	-13.50

The Panama Canal has two lakes: Gatun and Miraflores. Water from these two lakes is used for the Panama Canal System to fill the navigation locks. Salt water from the Pacific and Atlantic Oceans gets added to the lakes during the transit of the ships. In addition, water from the lakes is lost to the sea during the same process. The Gatun Lake supplies fresh water to the population of Panama, Colon, and Chorrera Cities for drinking purposes. The Miraflores Lake has a level of salinity which is already considered "brackish" water (i.e., Brackish water is water that has more salinity than fresh water, but not as much as seawater) (Parchure et al. 2000).

The six locks have different volumes and geometric characteristics so that ships of different drafts can cross the Panama Canal from the Pacific Ocean to Gatun Lake. Table 1 shows the dimensions of the locks and all levels, heights, and depths are referenced to the "Precise Panama Canal Level Reference" (PLD) that matches sea level.

Using the equations of exchange of salinity in the locks, it is possible to set a numerical and differential equations model to define the salinity in Gatun Lake (S_{GL}), taking into account the exchange of water (and salinity) in the upper locks of Pedro Miguel and Gatun, the water contribution by lakes Gatun (V_{GL}), the volumetric inflows of Madden (V_{Madden}) and the river tributaries (V_{trib}) that flow into these lakes (Parchure et al. 2000). Madden Lake is a reservoir of water which acts as additional water storage for the canal. V_{MT} is the summation of the volumetric inflows of V_{Madden} and V_{trib}. These relationships are expressed by the following equations were evaporation and precipitation are added due to their potential impact:

$$V_{MT} = V_{Madden} + V_{Trib} \tag{1}$$

$$\Delta V_{L3} = V_{L3} - VS \tag{2}$$

$$\Delta V_{L4} = V_{L4} - VS \tag{3}$$

$$\begin{aligned}\text{Losses(t)} = {} & \text{Evaporation (t)} - \text{Freshwater facilities (t)} - \text{Hydropower plan (t)} \\ & - \text{Panamax lockages}\end{aligned} \tag{4}$$

$$\frac{\partial(V_{GL})}{\partial t} = \Delta V_{MT} + \Delta V_{L3}.EX_{L3} + \Delta V_{L4}.EX_{L4} + \text{Precipitation (t)} - \text{Losses (t)} \tag{5}$$

$$\frac{\partial(S_{GL})}{\partial t} = \frac{V_{GL}.S_{GL} + (V_{MT}.S_{Madden}) + (\Delta \mathrm{V_{L3}}.S_{L3}.\mathrm{EX_{L3}}) + (\Delta \mathrm{V_{L4}}.S_{L4}.\mathrm{EX_{L4}})}{V_{GL} + V_{MT} + (\Delta \mathrm{V_{L3}}.\mathrm{N}.\mathrm{EX_{L3}}) + (\Delta \mathrm{V_{L4}}.\mathrm{N}.\mathrm{EX_{L4}})} \tag{6}$$

where V_{L3} and V_{L4} are the volumes of Locks L3 and L4 respectively. VS is the displacement volume of a ship (average). S_{L3} and S_{L4} are the respective salinities of L3 and L4 taking into consideration the measured salinity gradients. EX_{L3} and EX_{L4} are the exchange ratios for L3 and L4 respectively. Piecewise linear profiles of Evaporation and Precipitation are added to the calculations of V_{GL} (Marin et al. 2010). These differential equations are the basis of a system dynamics model that is formed by differential (first order) and algebraic equations.

3 DISCRETE-EVENT MODELING

Different interviews with different subject-matter experts (SMEs) to learn about the operations were performed in order to obtain the different distributions and times of the discrete-event processes. A discrete-event model was developed in AnyLogic (Rabelo et al. 2012), with the respective animations, Queues, Switches, Java Classes, and the Enterprise (i.e., discrete-event) Library. The Switches were complemented with Java statements to capture the logic of assignment of locks and the schedule of the Panama Canal. In addition, animation was added in order to support the visualization and validation by subject matter experts.

4 MODELING EVAPORATION THROUGH SUPPORT VECTOR REGRESSION (SVR)

Support vector regression (SVR) was used for estimating the evaporation level (Rabelo et al. 2012) by using as predictors: precipitation, temperature, humididy, salinity, windspeed and wind direction (Morton 1986; Price et al. 2007; Sadek, Shahin, and Stigter 2007). The historical data was obtained from the respective weather stations of the Panama Canal (2003 – 2009). The SVR is the regression version of support vector machines (SVMs) a well known supervised learning algorithm used for supervised classification and is based on separation by hyperplanes. In the regression setup we are given a set of m data point {(x_1,y_1), (x_2,y_2),…,(x_m,y_m)} where x_i∈R^n, i=**1,…,m** are the vector with the features and y_i∈R, i=**1,…,m** the output variable. Then under the support vector framework we wish to determine the optimal hyperplane defined by the parameters (w,b) as the optimal solution of the following convex optimization problem:

$$\begin{aligned} \min_{w,b,\xi_i,\xi_i^*} \quad & \frac{1}{2}w^T w + C\sum_{i=1}^{m}\xi_i + C\sum_{i=1}^{m}\xi_i^* \\ s.t \quad & w^T\phi(x_i) + b - y_i \le \epsilon + \xi_i \\ & y_i - w^T\phi(x_i) - b \le \epsilon + \xi_i^* \end{aligned} \tag{7}$$

where $\boldsymbol{\xi_i}, \boldsymbol{\xi_i^*} \geq \mathbf{0}, \boldsymbol{i} = \mathbf{1}, \dots, \boldsymbol{m}$. In addition, $\boldsymbol{w}$ is the weight vector and b is the bias. With $\boldsymbol{\phi}(.)$ we denote the kernel function. Through the kernel function we can generalize the method in nonlinear high dimensional spaces and thus overcome the limitations related to the linear nature of the basic formulation. Each feature was normalized in order to have zero mean and unitary standard deviation. This is a standard preprocessing step that allows all the predictors to have the same weight in the model. The output variable was left as it is since it doesn't affect the model training. The SVR implementation was libSVM as employed through Matlab (ver 2011b) interface. A radius basis function (RBF) kernel was used with parameter σ=0.25. At each step a sliding window was used in order to select the sample to train the algorithm. The window parameter was set to three. The average per sample square error $\boldsymbol{R^2}$ was found to be equal 0.0427 (or 4.27%). The short term prediction results are shown in the following Figure 3. This was compared with neural networks based on back propagation and radial-basis functions and the SVR was the one with higher performance.

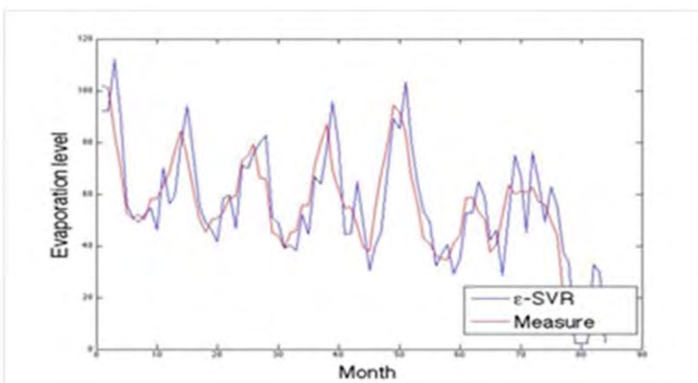

Figure 3: SVR's performance (evaporation).

5 MAPPING VOLUME TO HEIGHT (GATUN LAKE) USING NEURAL NETWORKS

The modeling of the Panama Canal Expansion includes IF-THEN rules based on the level of the lakes and the respective volumes. In order to facilitate the execution of these rules, we have to develop a mapping from the volume to the height of Gatun Lake. A neural network was developed to perform this mapping. The data was obtained from a comprehensive study of Gatun Lake (Bunch, Johnson, and Sarruff 2003). The observed data is based upon pre-impoundment surveys from the early 1900's and include estimation of changes that have occurred due to sedimentation in the last ninety years. The mapping is not straightforward because of Lake Gatun's irregular shape. The reported bathymetry of Lake Gatun with its numerous bends and small embayments is extremely difficult to match. Therefore, neural networks are good for this mapping.

The architecture is of one input (Volume in millions of cubic meters), two hidden-units in one single hidden layer, and one output (Height in meters) (Figure 4). It is basically a look-up table with high accuracy and easy to execute during the execution time of the hybrid model.

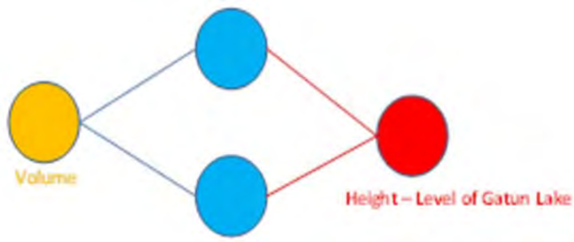

Figure 4: Neural network built to map volume to height (Gatun Lake).

6 HYBRID MODEL

The system dynamics model with the discrete-event model were combined into one model using the capabilities of the Active Object Class from AnyLogic (Borshchev and Filippov 2004; Karpov et al. 2005; Wartha et al. 2002). The Active Object Class from AnyLogic has multiple concurrent activities that share object local data and object interface. Activities can be created and destroyed at any moment of the model execution. The discrete-event model feeds the number

In addition, the output in salinity of our model is compared against two other models for salinity of the current Panama Canal (see Table 3). The model developed by the Army Corps of Engineers predicts the salinity in the years 2003 – 2009 to be stable at a value of 0.032 ppt (Parchure et al. 2000). The Army Corps of Engineers did not consider precipitation, evaporation, hydropower plants, fresh water facilities, and spillways flows. The other model was commissioned by the Panama Canal Authority to the company Delft Hydraulics (http://www.wldelft.nl/) (Jongeling 2003). This model does not consider precipitation and evaporation. In addition, this model uses a constant transit rate of 36 ships/day for the current Panama Canal. The hybrid model has a higher quality than the previous models.

Table 3: Accuracy in salinity simulations.

Measure	**Army Corps of Engineers Model**	**Delft Hydraulics Model**	**Hybrid Model**
Mean Absolute Error (MAE)	0.021	0.032	0.007
Mean Square Error (MSE)	0.00116	0.00189	0.00008
Mean Square Error (MSE)	0.00116	0.00189	0.00008
Root Mean Square Error (RMSE)	0.034	0.043	0.009
Percent Bias (PBIAS) (Moriasi, Arnold, Liew, Bingner, Harmel, and Veith 2007)	34.66%	64.27%	-5%

7 EXPANSION SIMULATION MODEL

We utilized the same logic and add for the Gatun Lake equations for the new set of locks being built for the expansion of the Panama Canal. The equations for the Miraflores Lake stayed the same. The new Post-Panamax locks are given by the following notation and Table 4:

L7: Lowest Post-Panamax lock connected to the Pacific Ocean
L8: Middle Post-Panamax Lock on the Pacific side
L9: Highest Post-Panamax Lock on the Pacific side directly connected to Gatun Lake
L10: Highest Post-Panamax Lock on Atlantic side directly connected to Gatun Lake
L11: Middle Post-Panamax lock on the Atlantic side
L12: Lowest Post-Panamax lock connected to the Atlantic Ocean

Table 4: Physical dimensions of the Panama Canal Post-Panamax Locks - Post-Panamax is a term for ships larger than Panamax that do not fit in the canal (Arias et al. 2006).

Lock	**Width (m) × Length (m)**	**Height over lock (m)**	**Depth under or over PLD (m)**
L7	55 × 427	8.83	-20.62
L8	55 × 427	17.37	-10.67
L9	55 × 427	25.91	-2.41
L10	55 × 427	25.91	-2.41
L11	55 × 427	17.30	-10.49
L12	55 × 427	8.68	-18.62

The Exchange Coefficients are different from the Panamax Locks due to the utilization of water saving basins (WSBs). EX_{L9} and EX_{L10} are the exchange ratios for L9 and L10 respectively that take into consideration the WSBs recycling (Arias et al. 2006). In addition, the losses of fresh water due to the lockages of the Post-Panamax Locks are reduced by a factor of 64% due to the WSBs. V_{PPs} is the volume of references for the Post-Panamax ships. Equations 8, 9, 10, and 11 show the additions with the Post-Panamax operations.

$$\Delta V_{L10} = V_{L10} - V_{pps} \tag{8}$$

$$\Delta V_{L10} = V_{L10} - V_{pps} \tag{9}$$

$$\begin{aligned} Losses = Evaporation(t) - Freshwater\ facilities(t) - Hydropower\ pln(t) \\ - (PostPanamax - Panamax) lockages \end{aligned} \tag{10}$$

$$\begin{aligned} \frac{\partial\ (\mathrm{VGL})}{\mathrm{dt}} = \Delta V_{MT} + \Delta V_{L3}.EX_{L3} + \Delta V_{L4}.EX_{L4} + \Delta V_{L9}.EX_{L9} + \Delta V_{L10}.EX_{L10} \\ + \mathrm{Precipitation\ (t)} - \mathrm{Losses\ (t)} \end{aligned} \tag{11}$$

Meetings with personnel of the Panama Canal Authority and projections of future transits of Post-Panamax ships were obtained. This supported the addition of the processes and rules to model the new Post-Panamax locks. The projections utilized for Post-Panamax traffic in the future are shown in Table 5.

Several additions were implemented into the model such as representations of the tides in the Pacific and Atlantic. The validation was just performed by using subject matter experts of the Panama Canal Authority. They agreed that the model approximates and obtains the projected transits of the Post-Panamax locks. The prediction of the salinity is also very logical in comparison with the other models. Results and comparisons with the Deft Hydraulics model (Jongeling 2003) are depicted in Figure 6.

Table 5: Daily (projected) traffic for the new Post-Panamax lane - Panamax Plus vessels are of Panamax size with more than 12.04 m of draft.

Type of Vessels	**Years: 2015-2020**	**Years: 2020-2025**	**Years: 2025-2030**
Panamax Plus	4	4	4
Post-Panamax		2	3
Total Daily Traffic	**4**	**6**	**7**

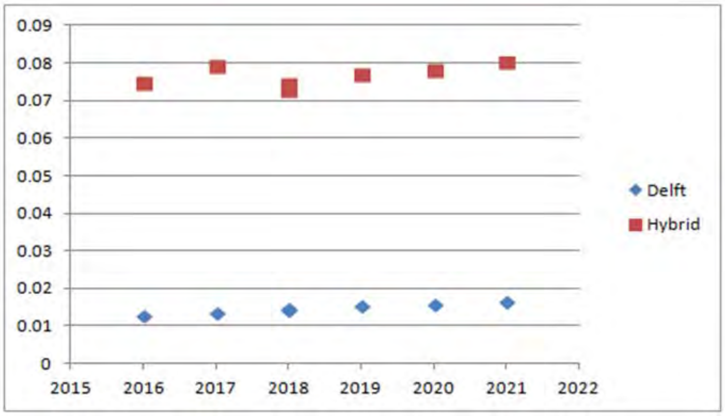

Figure 6: Comparison of the model of Delf Hidraulics (Jongeling 2003) and the Hybrid Model for the period from 2015 to 2022.

8 ENCAPSULATING THE HYBRID MODEL IN A NEURAL NETWORK (PRELIMINARY ANALYSIS)

The hybrid model was exercised and hundreds of data samples were generated in order to train a neural network. The reason was to build a neural network that was able to capture the knowledge of the hybrid model. This neural network can be replicated and executed using common user interfaces such as Excel and avoid the execution of simulation models using licensed software.

After the generation of 400 examples was accomplished, we decided to use a 2-step process. The first step is the utilization of principal component analysis (PCA) in order to determine the best combination of variables (and avoid problems and take advantage of larger variances). PCA is used to reduce the number of variables. In our case, we will perform PCA to generate some of most informative features. The second step is to build a neural network in order to have a “clone” model in a different mathematical form.

PCA is a mathematical procedure that uses an orthogonal transformation to convert a set of samples into a set of values of linearly uncorrelated variables called principal components. It is very clear that the number of principal components is less than or equal to the number of original variables. We have 35 variables in the generated data from the simulations. Some of these variables such as *Number_of_PostPanamax_Ships(t)* are studied including its previous values (up to three previous periods, e.g., *Number_of_PostPanamax_Ships(t-1)*, *Number_of_PostPanamax_Ships(t-2)*, *Number_of_PostPanamax_Ships(t-3)* where t (time) is by months) in order to capture trends and learn from the causality delays embedded in the system. The transformation from the PCA procedure is defined in such a way that the first principal component has the largest possible variance, and each succeeding component in turn has the highest variance possible under the constraint that it be orthogonal to the preceding components (http://yatani.jp/HCIstats/PCA).

MATLAB was utilized in order to obtain the principal components (strictly with data generated from the simulation model with 35 variables and 75% of the examples). The components with the largest variance were selected with the respective variables and factors. Table 6 shows the most significant principal components and the respective variables utilized to build the neural network.

10-fold crossvalidation (Moody 1994) was used with 75% (300) of the examples generated in order to develop an appropriate neural network. The performance capabilities of the neural network developed were tested with the remaining 25% (i.e., 100) examples.

The neural network architecture found using 10-fold crossvalidation had 14 input units (one for each principal component), 5 hidden units in one hidden layer, and one output unit (that corresponds to the increment of Salinity in Gatun Lake). Figure 7 depicts the neural network built using entirely simulated data and 300 training samples. The neural network had an average training error of 0.0005 ppt. On the other hand, the testing of the neural network developed with the testing set (i.e., 25% of the generated data) had an average testing error of 0.0023 ppt. In addition, the neural network with PCA was compared against a SVR without PCA. SVR had lower performance than the neural network with PCA.

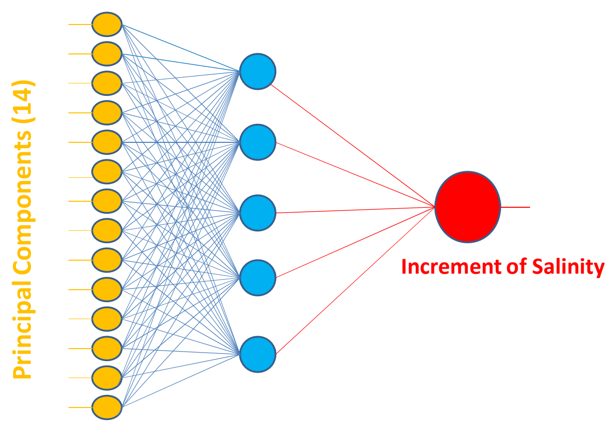

Figure 7: Neural network built to capture the knowledge of the hybrid simulation model (preliminary analysis).

Table 6: Preliminary PCA Analysis.

Principle Components			
PC 1	-0.206*Tributaries(t-3)* - 0.298*Tributaries (t-2)* - 0.315*Tributaries(t-1)* - 0.219*Tributaries(t)*- 0.26*Hydro_Water_Spillovers(t-3)* - 0.502*Hydro_Water_Spillovers(t-2)*- 0.544*Hydro_Water_Spillovers(t-1)* - 0.323*Hydro_Water_Spillovers(t)*	PC 8	0.338*Hydro_Water_Spillovers(t-3)*- 0.633*Hydro_Water_Spillovers(t-2)*+ 0.593*Hydro_Water_Spillovers(t-1)*- 0.353*Hydro_Water_Spillovers(t)*
PC 2	0.592*Hydro_Water_Spillovers(t-3)*+ 0.531*Hydro_Water_Spillovers(t-2)*- 0.291*Hydro_Water_Spillovers(t-1)*- 0.593*Hydro_Water_Spillovers(t)*	PC 9	0.65Number_of_*Panamax_Ships(t-3)*- 0.676Number_of_*Panamax_Ships(t-2)*+ 0.276Number_of_*Panamax_Ships(t-1)*- 0.2Number_of_*Panamax_Ships(t)*
PC 3	-0.603*Tributaries(t-3)* - 0.392*Tributaries (t-2)* + 0.299*Tributaries(t-1)* + 0.4571*Tributaries(t)*+	PC 10	-0.507Number_of_*Panamax_Ships(t-3)*+ 0.663Number_of_*Panamax_Ships(t-1)*– 0.547Number_of_*Panamax_Ships(t)*

	0.277*Hydro_Water_Spillovers(t-2)*- 0.322*Hydro_Water_Spillovers(t)*		
PC 4	0.47*Tributaries(t-1)*+ 0.485*Hydro_Water_Spillovers(t-3)* - 0.365*Hydro_Water_Spillovers(t-2)*- 0.479*Hydro_Water_Spillovers(t-1)* + 0.341*Hydro_Water_Spillovers(t)*	PC 11	0.53Number_of_*Panamax_Ships(t-3)*+ 0.68Number_of_*Panamax_Ships(t-2)*– 0.501Number_of_*Panamax_Ships(t)*
PC 5	-0.436*Tributaries(t-3)* + 0.346*Tributaries (t-2)* + 0.331*Tributaries(t-1)* - 0.514*Tributaries(t)*	PC 12	-0.693Number_of_*Panamax_Ships(t-1)*- 0.637Number_of_*Panamax_Ships(t)*
PC 6	0.315*Tributaries(t-3)* + 0.309*Tributaries (t-2)* + 0.308*Tributaries(t-1)* + 0.304*Tributaries(t)*	PC 13	0.51Number_of_Post*Panamax_Ships(t-3)*+ 0.55Number_of_Post*Panamax_Ships(t-2)* + 0.510Number_of_Post*Panamax_Ships(t-1)*+ 0.392Number_of_Post*Panamax_Ships(t)*
PC 7	0.481*Tributaries(t-3)* + 0.316*Tributaries(t-1)* + 0.445*Tributaries(t)*- 0.448*Hydro_Water_Spillovers(t-3)*- 0.391*Hydro_Water_Spillovers(t)*	PC 14	0.719Number_of_Post*Panamax_Ships(t-3)*+ 0.669Number_of_Post*Panamax_Ships(t)*

9 CONCLUSIONS AND FURTHER RESEARCH

This research provides a unique example for applying hybrid modeling. Hybrid modeling can benefit organizations with complex systems by providing them with a modeling environment which takes into account the internal and external changes taking place in their systems where continuous and discrete variables are present.

AI methods support modeling by mapping complex relationships. In addition, these methods can encapsulate the knowledge of the simulation models and facilitate their utilization and replication. Currently, we are refining the model and adding more animations. Different scenarios with the Post-Panamax locks are also being simulated. In addition, we are adding elements of the variability of the salinity levels in each ocean (i.e., the Pacific and Atlantic oceans have different levels and seasonality patterns of salinity) and a mixed of historical observations with a higher number of examples generated by the simulations to the PCA analysis. We will report in future papers the results of these developments.

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REFERENCES

Alvarez, H., D. Solis, L. Rabelo, and A. Cano. 2009. "The System Dynamics Simulation of the Expansion of the Panama Canal." *International Journal of Technology, Policy and Management* 9(1): 17–28.

Arias, A., C. Kiamco, J. Regge, and J. Gouverneur. 2006. "Conceptual Design of New Post-Panamax Locks in the Panama Canal." In *Proceedings of the Permanent International Association of Navigation Congresses (PIANC) Congress*.

Borshchev, A. and A. Filippov. 2004. "From System Dynamics and Discrete Event to Practical Agent Based Modeling: Reasons, Techniques, Tools." In *Proceedings of the 22nd International Conference of the System Dynamics Society*, 25-29.

Bunch B., B. Johnson, and M. Sarruff. 2003. "Panama Lakes Water Quality Modeling Study." Report of the Army Corps of Engineering, - Engineer Research and Development Center, ERDC/EL TR-03-XX.

Jongeling T. 2003. "Salt Water Intrusion Analysis – Future Situation: Post-Panamax Locks." Report of Delft Hydraulics for the Panama Canal Authority.

Karpov, Y., R. Ivanovski, N. Voropai, and D. Popov. 2005. "Hierarchical Modeling of Electric Power System Expansion by AnyLogic Simulation Software." In *Proceedings of the 2005 IEEE PowerTech*.

Marin, M., Y. Zhu, L. Andrade, E. Atencio, C. Boya, and L. Rabelo. 2010. "Supply Chain and Hybrid Modeling: The Panama Canal Operations and its Salinity Diffusion." In *Proceedings of the 2010 Winter Simulation Conference*, edited by B. Johansson, S. Jain, J. Montoya-Torres, J. Hugan, and E. Yücesan, 2023-2033. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Moody, J. 1994. "The Effective Number of Parameters: An Analysis of Generalization and Regularization in Nonlinear Learning Systems." In *Advances in Neural Information Processing Systems*, edited by J. Moody, S. Hanson, and R. Lippmann, 4:683-690. Morgan Kaufman Publishers, Inc.

Moriasi, D., J. Arnold, M. Liew, R. Bingner, R. Harmel, and T. Veith. 2007. "Model Evaluation Guidelines for Systematic Quatification of Accuracy in Watershed Simulations." *Transactions of the ASABE* 50 (3): 885-900.

Morton, F. 1986. "Practical Estimates of Lake Evaporation." *Journal of Climate and Applied Meteorology* 25(3): 371–387.

Panama Canal Authority. 2006. "Proposal for the Expansion of the Panama Canal: Third Set of Locks Project." Available from: http://www.pancanal.com/eng/plan/documentos/propuesta/acp-expansion-proposal.pdf. Accessed 10 July 2013.

Parchure, T., S. Whilhelms, S. Sarruff, and W. McAnally. 2000. "Salinity Intrusion in the Panama Canal." Report, Coastal and Hydraulics Laboratory, U.S. Army Engineer Research and Development Center, US Army Corps of Engineers.

Price, R., W. Nuttle, B. Cosby, and P. Swart. 2007. "Variation and uncertainty in evaporation from a subtropical estuary, Florida Bay." *Estuaries and Coasts* 30(3): 497-506.

Rabelo, L., L. Andrade, P. Xanthopoulos, and M. Marin. 2012. "Expansion of the Panama Canal: Simulation Modeling and Artificial Intelligence." In *Proceedings of the 2012 Industrial and Systems Engineering Research Conference*, edited by G. Lim and J. W. Herrmann.

Rabelo, L., L. Andrade, E. Atencio, R. Collins, P. Xanthopoulos, M. Marin, C. Arellano, P. Coiduras, and B. Campos. 2012. "Preliminary Hybrid Modeling of the Panama Canal: Operations and Salinity Diffusion." *Modeling and Simulation in Engineering*, 2012: Article 806139.

Sadek, M., M. Shahin, and C. Stigter. 2007. "Evaporation from the reservoir of the High Aswan Dam, Egypt: A new comparison of relevant methods with limited data." *Theoretical and Applied Climatology* 56 (1-2): 57-66.

Sandoval, Y. 2005. "The Dilemma of the Expansion Costs." *Martes Financiero – La Prensa* 409(17): 24-28.

Wartha, C., M. Peev, A. Borshchev, and A. Filippov. 2002. "Decision Support Tool - Supply Chain." In *Proceedings of the 2002 Winter Simulation Conference*, edited by E. Yücesan, C.-H. Chen, J. L. Snowdon, and J. M. Charnes, 1297-1301. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

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