Artificial Neural Network for Sacramento–San Joaquin Delta Flow–Salinity Relationship for CalSim 3.0

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Abstract: The California State Water Project (SWP) along with the Central Valley Project (CVP), under various environmental regulations, manage California's complex water storage and delivery system. An important part of the water system regulations strictly limit salinity intrusion into the Sacramento–San Joaquin Delta, which is a complex tidal estuary with many factors influencing its salinity. The nonlinear relationship of these factors on salinity make the system operations challenging. Operational models [e.g., California Water Resources Simulation Model (CalSim) and CalSim Lite (CalLite)] are used to provide guidelines to decision makers for efficient planning and management of the system. But these operational models are not designed to directly simulate the salinity. The hydrodynamic and water quality model, California Department of Water Resources (DWR) Delta Simulation Model II (DSM2), is needed to simulate the salinity. Because of a linking problem and longer simulation time of DMS2, it is impractical to use DSM2 directly in operational models. This paper presents the development, improvement, and successful application of an artificial neural network (ANN). The ANN, when fully integrated into CalSim and CalLite, emulates the Delta salinity so that the operational models, when coupled with the ANN, can simulate the salinity management in the Delta. The newly developed and improved ANN reported in this research, when used in the CalSim model, provides more accurate insights on the salinity regime in the Delta, which is conducive to more efficient use of the freshwater in the Delta resulting in the more efficient overall operation of the SWP and CVP. **DOI: 10.1061/(ASCE)WR.1943-5452.0001192.**

Introduction

The Sacramento–San Joaquin Delta is a valuable part of California's complex water system, and it receives over 40% of the California state's runoff from Sacramento, San Joaquin, Mokelumne, Cosumnes, and Calaveras Rivers (Delta Overview 2019). It is the major collection point of water that serves more than 25 million people. The Delta itself is also a major part of agriculture, urban, industrial, environmental, and recreational activities. The Delta also serves as a habitat for many species of fish, birds, mammals, and plants.

Two major water management projects operate and manage California water system. The California State Water Project (SWP) is constructed and operated by the California Department of Water Resources (DWR). The SWP manages water storage and a delivery system of reservoirs, aqueducts, power plants, and pumping plants. It is the US's largest state-built, multipurpose, user-financed water project. It supplies water to more than 27 million people in northern California, the Bay Area, the San Joaquin Valley, the central coast, and southern California. The SWP water also irrigates about 303,514 ha (750,000 acres) of farmland, mainly in the San Joaquin Valley.

The SWP shares many facilities with the federal Central Valley Project (CVP), which primarily serves agricultural users. Water can be interchanged between the SWP and CVP canals as needed to meet various system requirements.

Some challenges faced by the planners and operators of the State SWP and CVP are to meet the ecological, flow, and salinity regulatory requirements while fulfilling the water rights requirements of all water right holders in the Central Valley. To maintain the Delta water quality, the water projects are operated under strict guidelines described in the revised Water Right Decision 1641 (State Water Resources Control Board 2000) issued by the State Water Resources Control Board in 2000. There are several salinity compliance locations where salinity, defined in chloride level terms of electrical conductivity (EC), is maintained to keep the Delta water quality in compliance (Fig. 1).

Delta salinity is affected by several factors. Variation in Delta water levels during each day caused by changing San Francisco Bay tides has a significant effect on Delta salinity by moving ocean salinity in and out of the Delta. Delta salinity levels are also influenced by the amount of flow moving toward the ocean. The higher the outflow is, of course, the less salinity intrusion into the Delta. Salinity levels in different locations can also be affected by various gate operations. The artificial neural network (ANN) described in this paper includes these major effects of the changing water levels caused by tidal action, Sacramento and San Joaquin River flows, Delta cross-channel operations, in-Delta diversions/returns, and water exports through the Delta to southern California.

The ANNs used in previous version of CalSim (CalSim II) were trained using a shorter period of time (water years 1974–1991). This period includes two historically dry periods (1975–1977, and 1986–1992). It was observed, however, that these ANNs were not performing well in 1928–1934, another important dry period in planning. In addition, the old ANNs (developed using CalSim II) were not performing well in the new CalSim 3.0 model. Therefore, there was a need to develop new and better performing ANNs for

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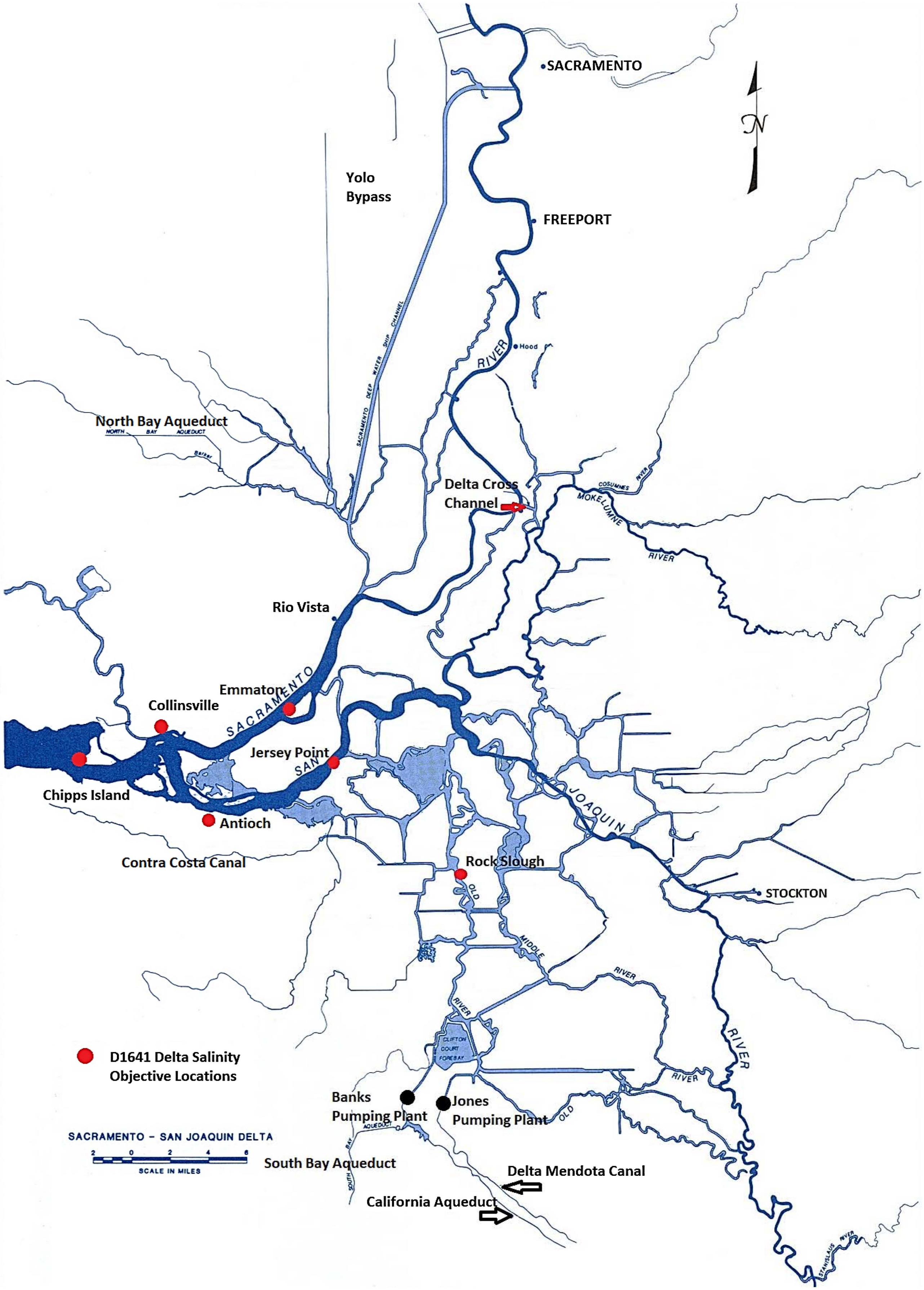

Fig. 1. D1641 Delta salinity objective locations. (Map adapted from Delta Atlas 1995.)

CalSim 3.0. The development of this flow–salinity relationship and improvement from the previous version are the focus of this paper.

Background

The California Water Resources Simulation Model (CalSim) (Draper et al. 2004) is a comprehensive modeling tool used to evaluate operation alternatives for the SWP and CVP systems. The projects' operations include the reservoirs, streams, aqueducts, and water exports to southern California. The CalSim simulated results are used with other models for longer-term operations decision support, such as for evaluating allocation decisions early in the water year by operators and managers of the SWP and CVP. CalSim is also used to evaluate systemwide effects of proposed structural and operational changes to the SWP and CVP. Results of these longer-term planning simulations are used to support analysis to meet requirements for the National Environmental Policy Act (NEPA) and California Environmental Quality Act (CEQA).

CalSim simulates reservoir operations and export levels while maintaining minimum flow requirements in streams and meeting the D1641 regulations that include salinity objectives at specified Delta locations (State Water Resources Control Board 2000). This requires solving an inverse problem that needs to predict flow required to meet a given salinity level. This inverse flow–salinity relationship, when successfully developed, is made to be a part of the CalSim model to meet the salinity objectives.

A hydrodynamic and water-quality model (DWR-DSM2 2019), is used to simulate Delta salinity. DSM2 is a river, estuary, and land modeling system used to calculate flows, stages, and flow velocities using the hydrodynamic module HYDRO. The DSM2 water-quality module, QUAL can be used to calculate many mass transport processes, including salts, multiple nonconservative constituents, temperature, trihalomethane (THM) formation potential, and individual particles. DSM2 is used to simulate salinity movement in the Delta using Sacramento and San Joaquin River flows and San Francisco Bay tidal fluctuations. Use of DSM2 to simulate salinity in an operational model, such as CalSim, is a challenge because DSM2 has longer simulation times. To simulate salinity as a function of flows, DSM2 would have to be run multiple times in an iterative manner, further extending the simulation time. As a result, it is necessary to have a method to represent DSM2 salinity in the CalSim model, so the concept of modeling a model.

In this paper, ANN models DSM2 so that very complex physical processes in the Delta are faithfully represented by ANN within CalSim. Because the salinity of the Delta is a nonlinear relationship of several aforementioned factors mentioned, a flow–salinity relationship ANN is used to imitate DSM2 simulated salinity in CalSim. The ANN is trained using DSM2-simulated salinity data for a given CalSim operation level flow.

Sacramento–San Joaquin Delta

The Sacramento–San Joaquin Delta is an important agricultural, ecological, and economic resource for California. The Delta is at the western edge of California's Central Valley, formed by the Sacramento River and San Joaquin River. The Delta covers 298,658 ha (738,000 acres) interlaced with hundreds of kilometers (miles) of waterways. Much of the land is below sea level and relies on more than 1,600 km (1,000 mi) of levees for protection against flooding. The Delta is a unique and valuable resource, and an integral part of California's water system. It receives runoff from 40% of the state's land area. That includes water that flows into the Sacramento, San Joaquin, Cosumnes, Mokelumne, and Calaveras Rivers (Delta Atlas 1995). Its land and waterways support communities, agriculture, and recreation and is the focal point for water distribution throughout the state.

The Delta is a tidal estuary. Water levels vary greatly during each tidal cycle, from less than 0.3 m (1 ft) near Sacramento to more than 1.5 m (5 ft) at Martinez. During the tidal cycle, flows can vary in direction and amount. Tidal action and Delta outflow creates a gradual salinity gradient from the Pacific Ocean into the interior Delta.

State (SWP) and federal (CVP) projects transport water from northern and central California reservoirs to southern California through the Delta. SWP include the California Aqueduct, the Harvey O. Banks Delta Pumping Plant, and North and South Bay Aqueducts. CVP major facilities include Jones Pumping Plant, Delta-Mendota Canal, and Contra Costa Canal (Delta Atlas 1995; Reclamation 2016). Appropriate salinity levels for drinking water quality and agricultural water quality are maintained by meeting or being below the D1641 objectives. Additionally, there are ecological salinity location objectives that need to be met. During times when flows are not enough to meet objectives, flows must be released from upstream reservoirs, or exports be decreased, to push the salinity toward the ocean, west of the Delta. To achieve better water quality, more flow needs to move toward the ocean, leaving less for exports.

Two major water export facilities are dependent on Delta waterways and the levees. Banks Pumping Plant provides water to the SWP via the California Aqueduct, and the Jones (formerly, Tracy) Pumping Plant provides water to the CVP via the Delta-Mendota Canal. These water projects are operated under strict guidelines in D1641. Upstream reservoir releases, Delta cross-channel operation, and amount of pumping are controlled to satisfy the standards in D1641.

California Water Resources Simulation Model, CalSim

Water Resources Integrated Modeling System (WRIMS) is a generalized water resources simulation model for evaluating alternatives in a water resources system. CalSim is an application of WRIMS, used as a planning tool to simulate the SWP and the CVP. CalSim has been applied to simulate the SWP and CVP systems at various levels of development, system configurations, demand scenarios, and operations rules. One operation rule is meeting the salinity standards imposed at various locations in the Delta to protect the environment. CalSim operates with following conditions:

- SWP and CVP water projects are operated under strict guidelines of Bay Delta Standards as described in the D1641 decision.
- Upstream reservoir releases, Delta cross-channel operation, and the amount of pumping are controlled to satisfy the standards in D1641.
- Salinity standards are imposed at various locations in the Delta to protect the environment and water uses of the Delta.
- In addition to the salinity locations, X2 (approximate location of 2,000 parts per million total dissolved solids) locations are specified during certain months of the year. Although the X2 location simulation is included in CalSim 3.0 ANN, it is not discussed in this paper.

CalSim II was used to simulate operations for the period of 1922–2003. CalSim 3.0 extended the simulation period through 2015.

Neural Network Use in Water Quality Modeling

ANNs have been applied in water resources modeling for years. A feedforward ANN has been used to compute water quality index in the Kinta River, Malaysia (Gazzaz et al. 2012). A single hidden layer feedforward neural network with precipitation, stream flow rate, and turbidity has been used as input to predict the suspended-solid level of small streams (Bowers and Shedrow 2000). Salinity prediction of River Murray of South Australia was done using a neural network (Maier and Dandy 1996). In the River Murray, salinity transport time was predicted from one location to another as a function of flow and upstream salinity.

An ANN model with multiple inputs has been successfully adopted to predict salinity in Suisun Bay and western parts of the Delta (Rath et al. 2001; Hutton et al. 2014). This was a refined Delta salinity empirical model. To achieve better results, the model structure used a hybrid approach that integrated neural networks within an existing empirical modeling framework. A longer time period (1922–2012) of observed salinity data was used, along with daily inflows to the Delta, mean costal water level, and daily tidal change, to train the ANN. In this study, ANN modeling results were compared with an empirical model (Hutton et al. 2016).

Delta salinity simulation is a multi-input, nonlinear, complex problem. Using a large number of parameters is very powerful in machine learning. Furthermore, although there is a possibility to overfit or overtrain, there are ways of preventing overfitting (Srivastava et al. 2014). A case study of Delta salinity by Chen et al. (2018) used ANNs similar to the study presented in this paper. In the Chen et al. (2018) study, ANNs used to emulate DSM2 were trained using a wide range of South Delta Barrier operations, Delta cross-channel operations, and Delta inflow.

Models Used in the Delta

Because CalSim is an operational model, it cannot be used to directly calculate the salinity. As a result, a salinity calculation model is required to use in CalSim. DSM2 can be used, but a longer simulation time restricts using DSM2 directly in CalSim.

Earlier attempts of Delta salinity modeling involved a net Delta outflow (NDO) salinity relationship. Time-lagged NDO as memory was used as the only input (Sandhu and Finch 1996a) in this modeling process. But a NDO-only model cannot say anything about the effect of rim-flow combinations and gate operations. As a result, a model is needed that can handle multiple inputs and nonlinear behavior.

Delta salinity depends on many variables including San Francisco Bay tidal effect, Sacramento River flow, San Joaquin River flow, Delta consumptive use, Delta diversions, return flow from agricultural lands, and Delta cross-channel operations. In 1995, DWR's Delta Modeling Section investigated ANN as an alternative to conventional techniques. ANNs are widely used for this type of multiple nonlinear regression relationships. ANNs that are trained using DSM2-simulated data with CalSim operational flows can be used to represent DSM2 salinity in the CalSim model.

Statistical Models

None of the established Delta water quality models could be used in an operational model, such as CalSim, to compute salinity at control locations because of long computation times. As a result, statistical models were used in the past within these operational models to predict the salinity. One of the earliest methods developed by the California DWR was the salinity-export curve (Department of Water Resources, Flow-salinity and exports, unpublished report). In the early 1990s a Delta outflow versus salinity relationship model (G-Model) (Denton 1993; Denton and Sullivan 1993) was used to predict salinity at Emmaton and Jersey Point. This model used net Delta outflow to predict EC. But it did not consider Delta cross-channel operation. The Delta cross-channel operation directly affected salinity at Emmaton and Jersey Point. In 2001, ANN was incorporated into CalSim. Comparison of studies using G-model and ANN (Mierzwa 2002) showed that ANN performed better.

Delta Island Consumptive Use and Delta Channel Depletion

Delta Island consumptive use is a necessary input for the DSM2 model. In the CalSim II model, Delta Island consumptive use values were estimated using the Consumptive Use model (CU model). The CU model estimated channel depletion as a single value for the whole Delta based on uplands and lowlands. The Adjusted Delta Island Consumptive Use (Anderson 2004) model was used to disaggregate the CU model results into 258 DSM2 nodes. The Adjusted Delta Island Consumptive Use model provided daily irrigation, drainage, and seepage values in each of 258 DSM2 nodes. It used historical patterns of distribution to disaggregate the net consumptive use. In CalSim, the 258 nodal values are divided into seven Delta subregions accretion/depletion values. This may not be an accurate method because there may be localized variations.

To overcome this problem, CalSim 3.0 used Delta Channel Depletion (DCD) model (Liang and Suits 2018). The DCD Model uses 168 subregions of the Delta in calculating consumptive use. DCD is an extension of the Delta Evapotranspiration of Applied Water (DETAW) model (Liang and Suits 2017). Based on the estimation of Delta ground surface water balance by DETAW, DCD simulates the daily channel depletions, including diversions, drainages, and seepages in the Delta, and distributes them on the DSM2 nodes. The advantage of using DCD is that it estimates the Delta channel depletion more accurately compared with the CU model. DCD model results with 2015 land use is used in CalSim 3.0.

Methods

Choosing a Type of Neural Network for CalSim

ANNs are computational models that work similar to the human nervous system. ANNs can be used in many areas including pattern recognition. If properly trained, they learn the patterns from data and can be used for predictions.

ANNs can be used to model any linear or nonlinear function. Once calibrated, ANNs are fast and reasonably accurate (Sandhu and Finch 1996a). ANNs consist of artificial neurons or mathematical models (function). Individual artificial neurons are interconnected with standardized topographies. Different types of ANN topographies are suited for solving different types of problems. ANNs have been used in areas such as process control, chemistry, gaming, radar systems, automotive industry, space industry, astronomy, genetics, banking, and fraud detection. ANNs have also been used for solving problems such as function approximation, regression analysis, time-series prediction, classification, pattern recognition, decision making, data processing, filtering, and clustering (Krenker et al. 2011).

There are several types of neural networks including feedforward neural networks, radial-basis function neural networks, Kohonen self-organizing neural networks, recurrent neural networks, convolutional neural networks, and modular neural networks. Currently, very complex methods, such as the Neural Turning Machine, are available (Tchircoff 2017).

At the time DWR developed the Delta flow–salinity relationship, the feedforward network and an earlier version of the recurrent network were available. Direct use of the feedforward neural

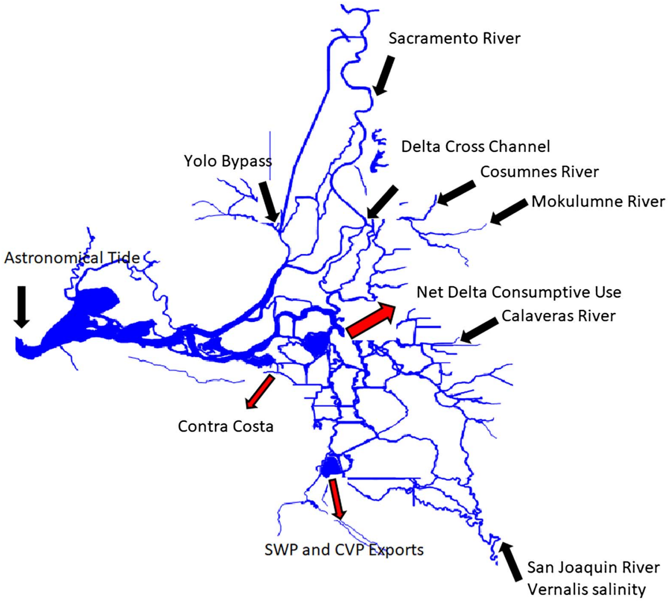

Fig. 2. ANN inputs and input locations. (Map adapted from Delta Atlas 1995.)

network was not successful. As a result, a feedforward network with input memory from preceding days was adopted in the Delta ANN (Sandhu and Finch 1996b). Delta ANNs are used to relate the flows to the salinity at interior and boundary locations in the Delta. Salinity data, in the form of electrical conductivity, are used from several locations of the Delta including Emmaton, Jersey Point, Old River at Rock Slough, and Collinsville.

In the Delta ANN training, 80% of the data are used for training and 20% of the data are used for validation. The training was determined to prevent overfitting. At this length of training period, the validation error reached the minimum.

Delta ANN Inputs and Outputs

The Delta flow–salinity relationship ANN uses seven daily inputs (Fig. 2):

- northern flow (Sacramento River, Yolo Bypass, Mokelumne River, Cosumnes River, and Calaveras River inflows),
- San Joaquin River flow,
- exports (Banks, Jones, and Contra Costa Pumping Plants),
- Delta cross-channel gate operation,
- net Delta consumptive use,
- tidal energy (daily maximum – daily minimum of astronomical tide), and
- San Joaquin River inflow salinity at Vernalis.

Delta ANN Structure

The neural network used in CalSim consists of an input layer, three hidden layers, and an output layer. The hidden layers consist of eight, two, and one neurons. The MATLAB 7.7.0 (R2008b) feedforward back-propagation tool newff was used with layer types logsig, logsig, and purelin in three hidden layers.

A fingerprinting study (Anderson 2002) for a constituent used in the DSM2 model showed that the daily Delta salinity depends on long-term memory of contributing parameters. Through an iterative process, it was determined that 117 antecedent days condition the influence on the current-day salinity. Through an iterative process,

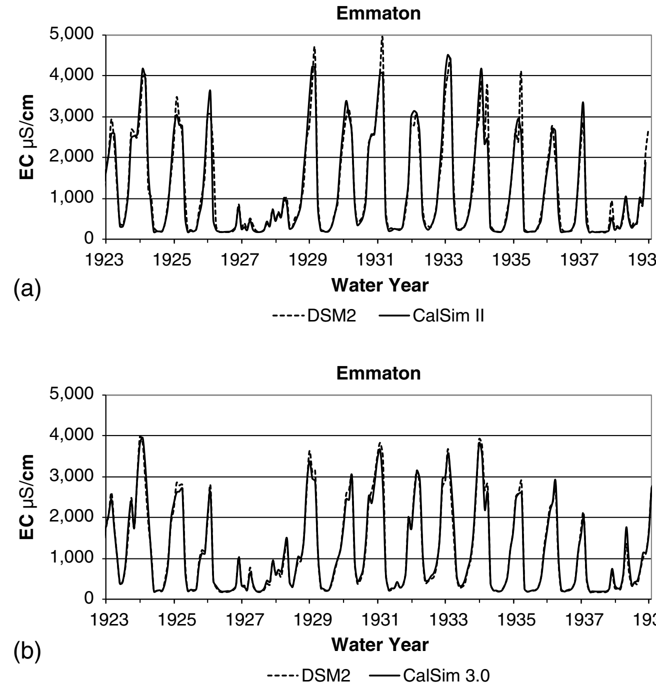

Fig. 3. (a) Simulated EC values with CalSim II at Emmaton; and (b) simulated EC values with CalSim 3.0 at Emmaton.

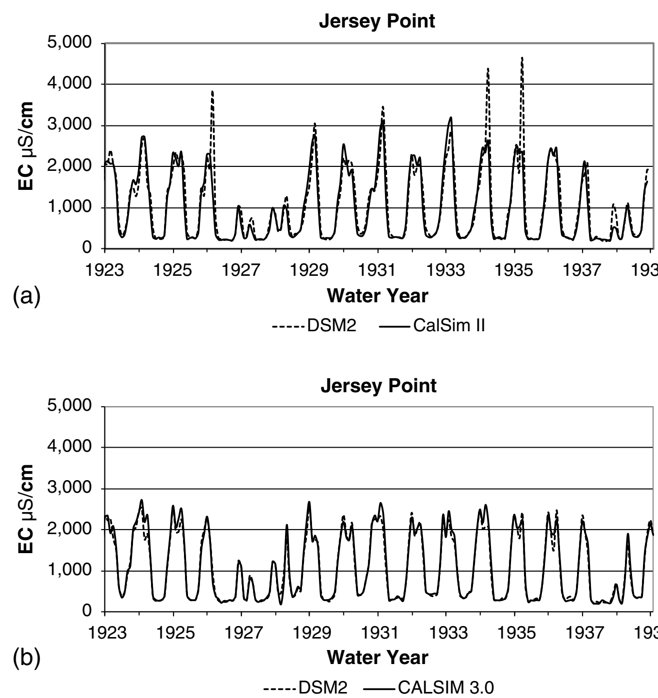

Fig. 4. (a) Simulated EC values with CalSim II at Jersey Point; and (b) simulated EC values with CalSim 3.0 at Jersey Point.

it was found that 4 antecedent days and 10 periods of 11-day averages give better simulated salinity results.

The current network structure of the ANN consists of 126 input nodes. Each node connects to a layer of eight internal hidden nodes that connect to a second layer of two internal hidden nodes and end with a single output node. The 126 values entered to the input

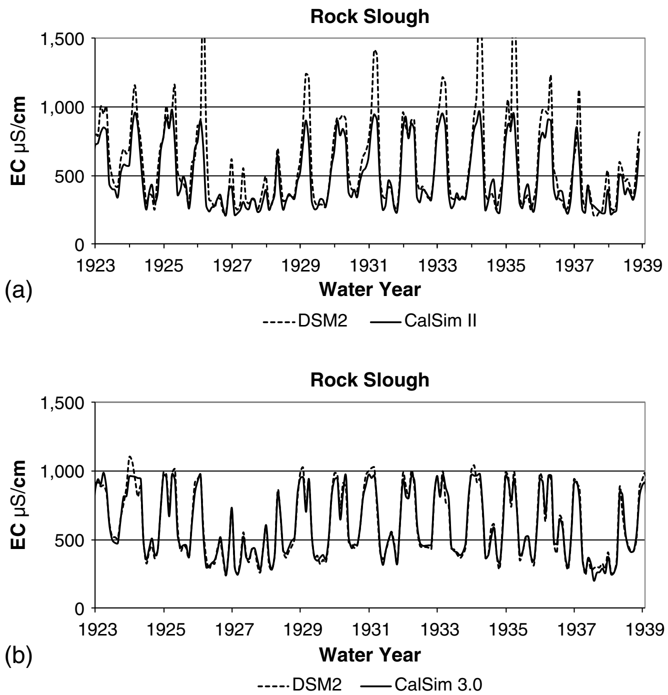

Fig. 5. (a) Simulated EC values with CalSim II at Rock Slough; and (b) simulated EC values with and CalSim 3.0 at Rock Slough.

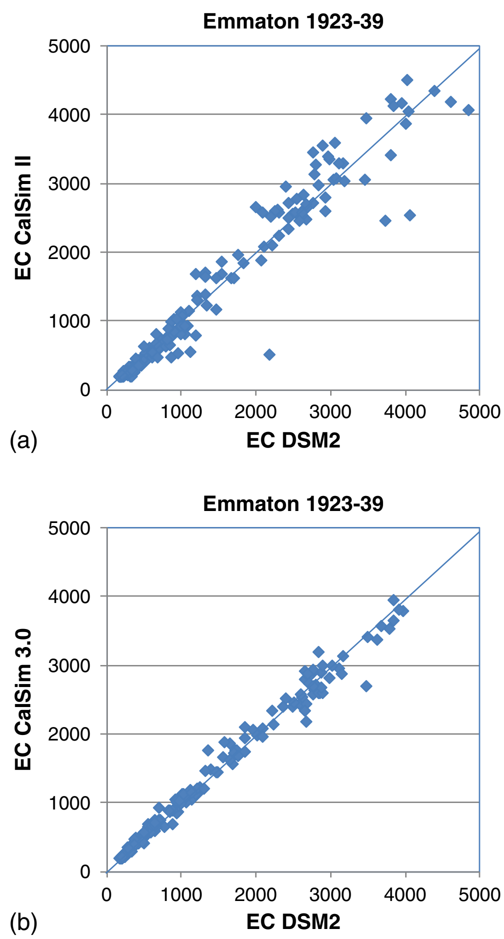

Fig. 6. (a) Simulated EC for DSM2 versus CalSim II at Emmaton for the validation period 1923–1939; and (b) simulated EC for DSM2 versus CalSim 3.0 at Emmaton for the validation period 1923–1939.

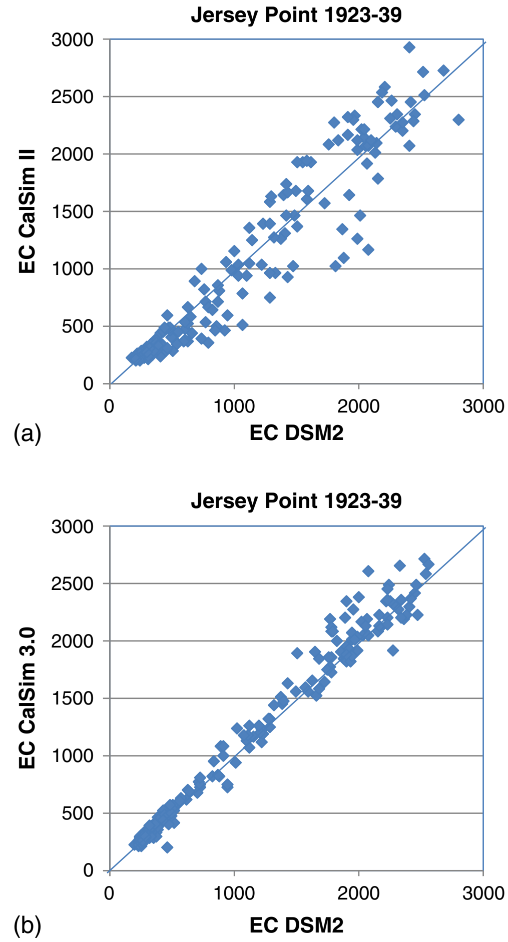

Fig. 7. (a) Simulated EC for DSM2 versus CalSim II at Jersey Point for the validation period 1923–1939; (b) simulated EC for DSM2 versus CalSim 3.0 at Jersey Point for the validation period 1923–1939.

nodes come from seven input sources, each with 18 input values. The 18 input values include current day + 7 days before current day + 10 averaged periods. Each period consists of 11 days.

Results

An ANN was trained to be used in the latest WRIMS application, CalSim 3.0 model. Compared with an older version of ANN (trained using CalSim II flow data 2010), the newly trained ANN produced better salinity results of DSM2-simulated salinity. In CalSim II, ANN training utilized four or five CalSim studies with the same 16-year period (water years 1974–1991). The new ANN is trained using flow data from a longer period of the same CalSim 3.0 study. Data from the water years 1940–2015 period are used in ANN training, whereas water years 1922–1939 are used as the validation period. Water years in California run from October 1 to September 30. In this new approach, the ANN experienced a wide range of hydrology including the 2011–2015 drought, which was the driest period in California record-keeping history (Hanak et al. 2016). The sum squared error criteria is used in evaluating the fit in calibration and validation data sets.

DSM2 versus ANN salinity [in the form of electrical conductivity (EC) in microsiemens per centimeter (μS/cm)] is compared for the newly trained Delta ANN (using CalSim 3.0 flow data) and

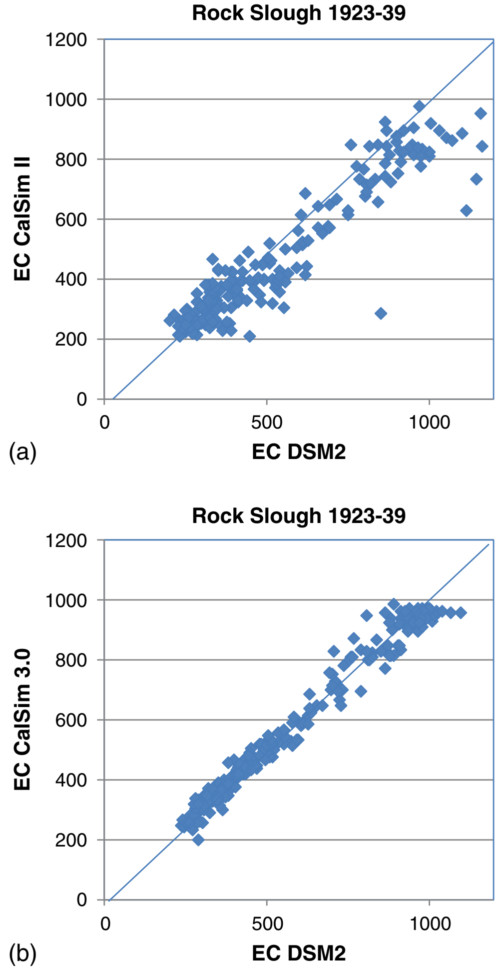

Fig. 8. (a) Simulated EC for DSM2 versus CalSim II at Rock Slough for the validation period 1923–1939; and (b) simulated EC for DSM2 versus CalSim 3.0 at Rock Slough for the validation period 1923–1939.

Table 1. Regression statistics (R^2) for CalSim 3.0 and CalSim II against DSM2 model simulated electrical conductivity values

	Calibration		Validation	
Station	CalSim 3.0 (1940–2015)	CalSim II (1974–1991)	CalSim 3.0 (1923–1939)	CalSim II (1923–1939)
Emmaton	0.994	0.966	0.988	0.953
Jersey Point	0.991	0.897	0.981	0.853
Rock Slough	0.984	0.830	0.973	0.701

the old Delta ANN trained (using CalSim II flow data) at the following locations: Emmaton, Jersey Point, Collinsville, Chipps Island, Antioch, and Rock Slough, the major locations of the Delta salinity compliances (Fig. 2). Discussions of the results are limited to Emmaton, Jersey Point, and Rock Slough, where the locations play a more important role in controlling project operations. These three locations are the most difficult locations to model due to their greater dependence on multiple flow factors. There is a significant improvement in EC prediction with the new ANN, as described subsequently.

Validation Period Results

Comparison of simulated salinity data for the validation period (water years 1923–1939) is shown in Figs. 3–5. In these figures, water year 1922 is not shown because it was considered as a warmup period for the DSM2 model simulation. All the DSM2 data presented in the figures are monthly averaged values. CalSim outputs are monthly values also. Compared with CalSim II, the new ANN (CalSim 3.0) simulated EC values are a better match with DSM2 results. Due to the longer training period (water years 1940–2015), the CalSim 3.0 ANN experiences a higher variation of flow including the 2011–2015 drought. This helps in predicting more accurate salinity during the validation period, which includes one of the driest periods, 1928–1934, in the recorded history.

Regression Plots

Monthly averaged DSM2 versus CalSim 3.0 monthly data for Emmaton, Jersey Point, and Rock Slough are plotted in Figs. 6–8 to compare the performance of CalSim 3.0 versus CalSim II. DSM2 versus ANN-simulated EC coefficient of determination (R^2) values as well as the relationship (trend line with 45°) were significantly improved for all three stations. Comparison of R^2 values from CalSim II and CalSim 3.0 are given in Table 1. Both calibration and validation period DSMm2 versus CalSim correlation is higher in CalSim 3.0. The R^2 values are significantly improved for Jersey Point and Rock Slough.

The system water balance comparison of new ANN with CalSim II ANN is given in Table 2. The system water balance is defined as Delta inflow = Delta outflow + Delta exports + Channel depletion/Delta island consumptive use + other losses which were not accounted for. To be consistent with CalSim II, the long-term comparison is done for the period of 1922–2003. Comparison of two historically dry periods (1929–1934 and 1987–1992) is also included in Table 2. There is no significant difference in system water balance in the two versions of the ANNs. The small difference in Delta inflow is mainly due to different

Table 2. Comparison of average annual system water balance of CalSim 3.0 and CalSim II [million m^3 (thousand acre-ft)]

Period	Model	Delta inflow	Delta outflow	Delta exports	CD/DICU
1922–2003	CalSim 3.0	26,610 (21,573)	19,918 (16,148)	5,939 (4,815)	766 (621)
	CalSim II	26,695 (21,642)	19,387 (15,717)	6,051 (4,906)	1,023 (829)
	Difference	−85 (−69)	532 (431)	−112 (−91)	−21.34 (−208)
	Difference (%)	−0.32	2.67	−1.89	−33.52
1929–1934	CalSim 3.0	12,415 (10,065)	7,353 (5,961)	3,816 (3,094)	975 (791)
	CalSim II	12,363 (10,023)	7,106 (5,761)	3,774 (3,060)	1,181 (957)
	Difference	53 (43)	247 (200)	42 (34)	−206 (−167)
	Difference (%)	0.43	3.36	1.1	−21.10
1987–1992	CalSim 3.0	13,346 (10,820)	8,460 (6,859)	3,642 (2,953)	950 (770)
	CalSim II	12,969 (10,514)	7,757 (6,289)	3,639 (2,950)	1,255 (1,018)
	Difference	376 (305)	703 (570)	4 (3)	−305 (−247)
	Difference (%)	2.87	8.31	0.1	−32.12

Note: CD = channel depletion; and DICU = Delta islands consumptive use.

consumptive use/channel depletion values used in the two versions of CalSim. With minimum difference of Delta inflow, exports, and Delta outflow, the new ANN (CalSim 3.0) provides better prediction of salinity in the given locations.

Conclusion

The old flow–salinity relationship ANNs used in CalSim II operational model to emulate DSM2 for the Sacramento–San Joaquin Delta were trained using a 16-year (water years 1974–1991) period. Old ANNs demonstrated better performance for the calibration/training period, but for the 1922–1939 validation period, the old ANNs were not as accurate in their predictions. In addition, the old ANNs were not compatible with the newly developed CalSim 3.0, which introduced changes, specifically more spatial details, regarding how certain Delta channels were represented. When the old ANNs were used in CalSim 3.0, the simulated salinity was not as comparable with the DSM2 simulated salinity, especially at Rock Slough and Jersey Point. These two locations play an important role in controlling State Water Project and Central Valley Project operations. Therefore, there was a need to develop a new set of ANNs for the Delta.

To overcome the problems faced in prior training, a longer period of calibration/training was used (1940–2015). The new training period included California's historically driest period of 2011–2015. In addition, the Delta Channel Depletion Model was used instead of the Consumptive Use model. With these modifications, successful ANNs were trained and used in CalSim 3.0. Comparison of salinity using new ANN in CalSim 3.0 and DSM2 was far superior to the ANN used in CalSim II. The modifications could be attributed for this superior performance. The ANNs when trained using a range of input flow can be reliably used in operational models to simulate the salinity management in the Delta.

Data Availability Statement

The following models used during the study are available online: CalSim 3.0 Model (https://water.ca.gov/Library/Modeling-and-Analysis/Central-Valley-models-and-tools/CalSim-3); DSM2 Model (http://baydeltaoffice.water.ca.gov/modeling/deltamodeling/models/dsm2/dsm2.cfm); DCD Model (https://water.ca.gov/Library/Modeling-and-Analysis/Bay-Delta-models-and-tools/DCD). The following data generated or used during the study are available from the corresponding author by request: input data used in artificial neural network training; output salinity data from DSM2 Model and CalSim 3.0 model.

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