International Proceedings of Chemical, Biological and Environmental Engineering, Vol. 97 (2016)
DOI: 10.7763/IPCBEE. 2016. V97. 7

Optimizing Canal Structure Operation in the Treasure Valley of Idaho

Andrew Campbell [1] and Jairo Hernandez [2 +]

[1] Boise State University Department of Civil Engineering, 1910 University Drive, Boise, ID 83705.

[2] Boise State University Department of Civil Engineering, 1910 University Drive, ERB 3135, Boise, ID 83705.

Abstract. A computer program proven to produce optimal operational rules for open-channel irrigation conveyance networks using synthetic data was tested using real world data. Operational rules are validated by satisfying variable demands while minimizing deviations from target water levels. The computer program uses an accuracy-based learning classifier system with an embedded genetic algorithm to produce optimal gate structure operations in irrigation canals. Rules are generated through the exploration and exploitation of a population of operation with the support of an unsteady-state hydraulic simulation model. Partial results are presented for discussion in this conference setting. This research is a step forward in optimizing water resources management in irrigations systems by automating irrigation control structures and providing water users with a flexible demand-based delivery scheme.

Keywords: hydraulic modeling, optimization, canal structure.

1. Introduction

Automation of irrigation canal control structures can provide a demand-based delivery scheme to deliver water to users more efficiently and with more flexibility than a rigid system. A flexible irrigation system provides flexibility in frequency, rate, and duration under control of the farmer [1]. Common practice in controlling irrigation control structures is to control each pool separately without accounting for the interactions between pools [2]. An optimization system is needed to minimize problems that arise as a result of using controllers that are designed to work in single pool applications.

Control algorithms have been developed to maintain stability in irrigation distribution networks under variable demands [3]. Previous work in this area produced rule-based canal gate operations from classifier systems supported by genetic algorithms (GA). Classifier systems are a type of machine learning system that uses a population of binary rules and, with the help of GA's, will select optimal rules given a set of inputs. A GA is a search heuristic procedure for optimization based on the theory of evolution and is used to solve complex problems [4]. Automation of irrigation control structures using traditional classifier systems [5] and accuracy-based classifier systems (XCS) [6] have been researched to maintain stable water levels and meet variable demands in multi-reach irrigation systems. XCS are adaptive systems that learn to perform the best action by interacting with an environment and assign a fitness metric to the rules based on the accuracy of the prediction and not the performance of the prediction. In the GA, parent rules transmit feature characteristics to new rules by reproduction, crossover, and mutation using "the survival of the fittest" principle. GA's have been used in reservoir operations for irrigation [7], cost optimization of water distribution systems design [8], drainage systems [9], water pipe replacement scheduling [10], irrigation water scheduling [11], optimal seasonal furrow irrigation [12], control valve location in pipe networks [13], in design of composite channels [14], and in optimization of irrigation control systems [5], [6].

+ Corresponding author. Tel.: + 208-426-3746; fax: 208-426-2351.
E-mail address: jairohernandez@boisestate.edu.

The use of classifier systems and GA's for automation of canal control structures have been tested using only synthetic data [5], [6]. The objective of this research was to determine the validity of an XCS with GA and find a set of optimal operational rules for control of an actual irrigation canal. The results from the hydraulic model are the inputs for the XCS and GA. The system of XCS, GA, and hydraulic model are known as "the model" from here on. The objective function for the model was to maintain a stable water level and meet the variable demands of the system by simultaneously controlling multiple structures through the network. Results from the simulations were compared to the historical data to determine how operational rules produced by the XCS performed.

2. Experimental

Physical characteristics of the Deer Flat Low Line (DFLL) canal and control structures along with historical flow data were required to create the model. Simplifications to the actual canal system were needed so that the model would converge to mathematical solution. Physical characteristics of the DFLL were obtained with help from the Boise Project and databases downloaded from the Idaho Department of Water Resources website. Parameters required in were: cross-section geometry, reach length, slope, and Manning's roughness coefficient, target water levels, and hydrographs at turnouts and at the source (Table 1). Canal network models previously created consisted of channels with rectangular shape, base widths of 1.0 m, side widths of 1.0 m, rectangular control gates, and reach lengths were never longer than 2000 m.

Table. 1: Deer Flat Low Line Canal Characteristics.

Parameter	Reach 1	Reach 2	Reach 3
Slope	0.00014	0.00032	0.00051
Length (m)	11,930	10,747	15,636
Depth (m)	2	2	1.5
Base width (m)	15.85	9.75	8.53
Side slope	1.5:1	1.5:1	1.5:1
Gate type	Radial gate	Radial gate	Rectangular gate
Number of gates	5	3	3
Width (m)	1.83	1.83	0.76
Height (m)	0.91	0.81	0.76

The development of a model using real-world information gave insight into constraints with the model system. Constraints in hydraulic model include: turnouts can be no further than ten thousand meters from the upstream end of a reach and initial condition must be steady-state. Constraints discovered with the model include: no bifurcations or confluences in the model, single gate control structures, one turnout per reach, demand and supply must be in the form of hydrographs, and there can be only three control structures in the system.

A single control structure was required in the model and the DFLL control structures were multiple gates side by side at the end of each reach. The modelled structure height was defined as the height of the actual structure and the width as the summation of actual widths. Some structure types were changed in order to create a stable model for analysis in the model. Reach one control structure was entered into the model as a radial gate; the same type that is present in the DFLL. A rectangular gate was used for structure two and a rectangular weir was used for structure three as shown in Table 1. The three reach system contained two control structures and a weir at the terminus.

Inflow to the system was input as a hydrograph, constant, and calculated. The expert operational control of the DFLL canal by the Boise Project created stable water levels for the majority of the simulation duration without changing control structure settings. A constant inflow was used to compare operations between the two scenarios.

Manning's roughness coefficients were determined from model calibration by comparing recorded upstream water levels and simulated water levels. Model characteristics are described in Table 2. Instances of model were run continuously. Actions were implemented, results were evaluated, rewards and penalties were applied, fitness was calculated, and the GA was applied to produce new classifiers. Simulations consisted of thousands of iterations, and with each iteration the population would increase in strength because the model would learn what would happen when actions were implemented on the environment.

Table. 2: Deer Flat Low Line Modelled Characteristics.

Parameter	Reach 1	Reach 2	Reach 3
Slope	0.00014	0.00032	0.00051
Length (m)	11,930	10,747	15,636
Depth (m)	2	2	1.5
Base width (m)	15.85	9.75	8.53
Side slope	1.5:1	1.5:1	1.5:1
Manning's n	0.016	0.016	0.016
Gate type	Radial gate	Rectangular gate	Weir
Number of gates	5	3	3
Width (m)	1.83	1.83	0.76
Height (m)	0.91	0.81	Open

3. Partial Results

Analysis of the up to date results found that gate operations only affected water levels at the downstream end of reaches. The model was modified to control water levels at the downstream end. Immediate changes were seen in graphical analysis of gate operations and downstream water levels. Target water levels were adjusted to correspond to the upstream water level data that was obtained from historical records. Several simulations were run with changes in target water levels, initial gate settings, and how the source flow was controlled. A summary of results for downstream control simulations is shown in Table 3.

Simulations took between three to ten days, running continuously, simulating the hydraulics of the network thousands of times. Tens of thousands of results files were produced during the simulations. Data was extracted and formatted from results files for analysis by a series of C# codes. The codes were used to look at water levels, water level deviations, and gate operations, all with respect to time steps. Paraview, a research data visualization software, and Microsoft Excel were used to render the data.

Table. 3: Downstream control simulation results: number of simulations, duration, final population size, initial and final average population fitness, and the maximum fitness of a classifier.

Model Name	Iterations	Clock time	Population	Average Fitness		Max. Fitness
				Initial	Final	
DFLL6vftag16DSF2	2325	6:07:00	35660	0.004	0.016	0.998

Simulation results from iteration 421 of the DFLLvftag16DSF2 model is shown in Fig. 1. Water level deviation decreased for reach 1 maintained a level inside the deadband nearly 75% of the simulated time under variable demand. The change in water level is inversely related to the change in gate operations. The effects of the gate operations can also be seen in the water levels in the Fig. 1. Time-steps are a calculated amount of simulated time based on the celerity in the reaches; it is not a constant value.

The fitness metric of the classifiers is used to gage how the model is predicting the action that is implemented on the environment. A higher fitness means that the model is learning what will happen in the system when a classifier is chosen. The average fitness of the population increases monotonically (Fig. 2)

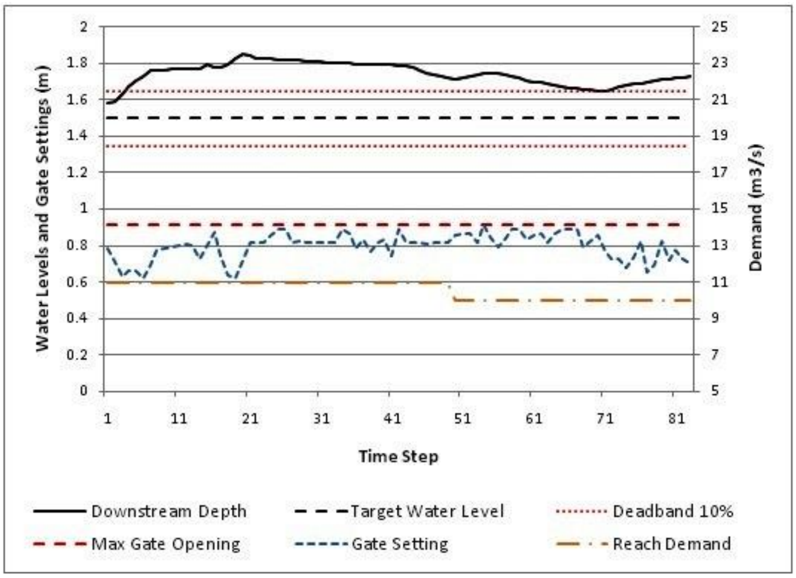

Fig. 1: Simulated water level, target water level, 10% deadband, gate setting chose by the model, and demand with respect to time step for best model iteration.

for simulations with downstream water level control.

The increase in the fitness of the population shows that the model is learning the outcome of the chosen action on the environment. The classifiers do not represent the actions that will provide a stable operation of the system, they represent the classifiers that the model can predict with near certainty what will happen in the system when the classifier is implemented. As more classifiers are evaluated and increase their fitness, the model will be able to learn what classifiers to choose to produce a certain action on the environment.

The historical data that was obtained was for an eight day period. Previous research used simulated time of less than 24 hours. To date, no model had completed the full duration of the eight day simulation time; several simulations have run through more than three days of historical data.

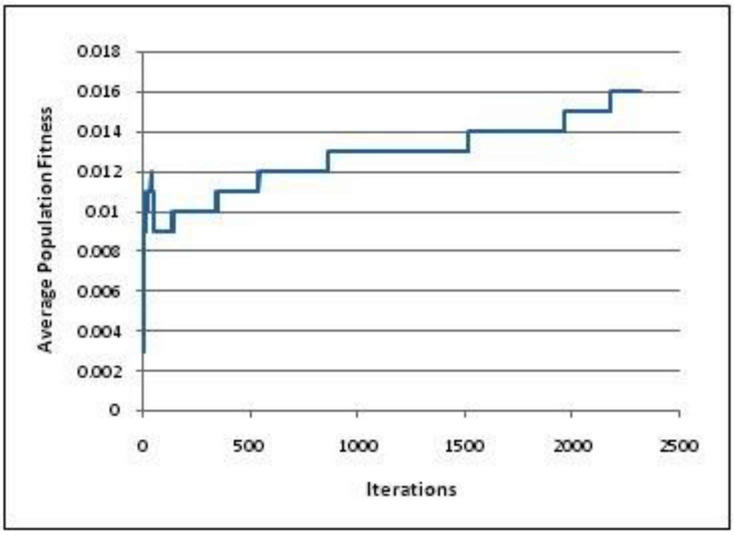

Fig. 2: Average population fitness with respect to the number of simulations for model DFLLvftag16DSF2.

4. Discussion

Results indicate that operational controls chosen by the model are controlling gates simultaneously and decreasing water level deviations in the system through simulated time. The longer the simulations are run the better the fitness of the population becomes. Classifier fitness increases to near maximum values indicating that the model is learning the response to the system when specific operations are implemented.

The model chose simultaneous gate operations that were implemented on the system to affect the hydraulics in the modeled canal network. While controlling multiple gates in the network simultaneously the model was able to reduce the water level deviations in the system in reach 1 and maintain water levels within the 10% deadband for 75% of the simulation time in simulation 421 for model DFLLvftag16DSF2.

Average population fitness increased monotonically in all simulations for downstream control. The model learned the responses from the system to actions as the number of simulations for each model increased. Although none of the simulations completed the full simulated duration, with more iterations a greater number of iterations will run for longer durations. The results show that as the model is run longer all aspects of the system perform better. Fitness increases over the population and the prediction of individual classifiers increases towards unity.

5. Conclusion

The model was used in previous research to find optimal operational rules for simultaneous control of a synthetic multi-reach irrigation network. This research tested the model's validity in an actual canal system while simultaneously controlling gate structures to maintain stable water levels and meet the demands of the irrigation canal system. The DFLL irrigation canal network in Canyon County, Idaho was modeled. The development of the model gave many insights in how to create large canal network models, simplifications that are needed, and constraints that exist in the model system.

Results show that the model was performing well with increasing average fitness parameter, maintaining water levels, and meeting user demands. Water levels in simulations improved towards the target levels with increased time steps in reach 1. Simultaneous gate operations reduced deviations in multiple reaches and supplied water to turnouts under variable demands. Increased fitness shows that the model is learning the response from the environment to actions that are performed. Rules were identified that the model could predict the effect on the system with near perfect accuracy. The number of rules that the effect on the environment could be accurately predicted increased with the number of simulation iterations. The next step is to add complexity to the model to make it more robust.

6. Acknowledgements

The authors would like to thank the Idaho EPSCoR and National Science Foundation award number EPS-0814387, Boise State University Department of Civil Engineering for support, the United State Bureau of Reclamation Boise Project Division 4 Office for the recorded data that was essential for this research, Tim Page, Assistant Project Manager of the Boise Project, and the ditch riders of Division 1 for the opportunity to ride along and help in taking field measurements.

7. References

[1] J.L. Merriam, S.W. Styles, and B.J. Freeman. (2007). "Flexible Irrigation Systems: Concept, Design, and Application." *Journal of Irrigation and Drainage Engineering*, **133**(1), 2–11.

[2] J.E. Hernández and G.P. Merkley. (2011). "Canal Structure Automation Rules Using an Accuracy-Based Learning Classifier System, a Genetic Algorithm, and a Hydraulic Simulation Model. II: Results." *Journal of Irrigation and Drainage Engineering*, **137**(1), 12–16.

[3] D. Rogers and J. Goussard. (1998). "Canal Control Algorithms Currently in Use." *Journal of Irrigation and Drainage Engineering*, **124**(1), 11–15.

[4] J.B. Nixon, G.C. Dandy and A.R. Simpson. (2001). "A genetic algorithm for optimizing off-farm irrigation scheduling." *Journal of Hydroinformatics* **3** (2001) 11-12

[5] S. Chittaladakorn and G.P. Merkley. (2005). "Classifier System for Rule-Based Operation of Canal Gates." *Journal of Water Resources Planning and Management*, **131**(1), 3–13.

[6] J.E. Hernández and G.P. Merkley. (2011). "Canal Structure Automation Rules Using an Accuracy-Based Learning

Classifier System, a Genetic Algorithm, and a Hydraulic Simulation Model. I: Design." *Journal of Irrigation and Drainage Engineering*, **137**(1), 1–11.

[7] D. Nagesh Kumar, K. Raju and B. Ashok. (2006). "Optimal Reservoir Operation for Irrigation of Multiple Crops Using Genetic Algorithms." *Journal of Irrigation and Drainage Engineering*, **132**(2), 123–129.

[8] A.V. Babayan, Z.S. Kapelan, A.D. Savic, and G.A. Walters. (2006). "Comparison of two methods for the stochastic least cost design of water distribution systems." *Engineering Optimization*, **38**(3), 281–297.

[9] W. Peng and R. Jia. (2004). "Improved genetic algorithms for optimal design of drainage systems." *Control, Automation, Robotics and Vision Conference*, 2004. ICARCV 2004 8th, 227 – 231 Vol. 1.

[10] G. Dandy and M. Engelhardt. (2001). "Optimal Scheduling of Water Pipe Replacement Using Genetic Algorithms." *Journal of Water Resources Planning and Management*, **127**(4), 214–223.

[11] Z.U. Haq and A.A. Anwar. (2010). "Irrigation Scheduling with Genetic Algorithms." *Journal of Irrigation and Drainage Engineering*, **136**(10), 704–714.

[12] P. Montesinos, E. Camacho and S. Alvarez. (2002). "Application of genetic algorithms for optimal seasonal furrow irrigation." *Journal of Hydroinformatics* **4** (2002) 145-156.

[13] L. Reis, R. Porto and F. Chaudhry. (1997). "Optimal Location of Control Valves in Pipe Networks by Genetic Algorithm." *Journal of Water Resources Planning and Management*, **123**(6), 317–326.

[14] A. Jain, R. Bhattacharjya and S. Sanaga. (2004). "Optimal Design of Composite Channels Using Genetic Algorithm." *Journal of Irrigation and Drainage Engineering*, **130**(4), 286–295.