Multi-Objective Evolutionary Algorithms in Water Resources Management

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Abstract

As a part of the WaterSMART Basin Study Program, PWRE worked on the Truckee Basin Water Management Options Pilot Study to develop flexible reservoir flood control operational criteria without increasing downstream flood risk. This study, among other things, evaluated Forecast Informed Reservoir Operations and flexible rule curves using a Multi-Objective Evolutionary Algorithm (MOEA) to optimize flood control regulation criteria and balance the tradeoffs between water supply, flood risk mitigation, and environmental flow objectives in the basin. This report documents the study and how MOEA provided a wholistic technical and decision-making framework that enabled stakeholders to develop alternative regulation criteria that optimally minimized risk and maximized benefits in the basin.

Introduction

Problems faced by water resource managers regularly necessitate decisions that balance the tradeoffs between multiple, often competing objectives. These problems, complex in nature, require a thorough technical approach to minimize the inherent risk in the decision. Multi-Objective Evolutionary Algorithms (MOEAs) provide an innovative, holistic decision-making framework in responding to these challenges. Fundamentally, MOEA aids water managers by thoroughly quantifying the tradeoffs between competing objectives, allowing them to minimize risk and maximize benefits in their decision-making.

As a part of the Truckee Basin Water Management Options Pilot Study (WMOP), Precision Water Resources Engineering (PWRE) worked alongside the United States Bureau of Reclamation (USBOR), Truckee Meadows Water Authority (TMWA), California Department of Water Resources (CADWR), Pyramid Lake Paiute Tribe (PLPT) and U.S. District Court Water Master of the Truckee River (collectively the Technical Team) to develop flexible reservoir flood control operational criteria without increasing downstream flood risk in the Truckee River Basin.

The current governing flood control regulation criteria in the Truckee River Basin is the US Army Corps of Engineers' (USACE) *Water Control Manual* (WCM). The WCM was adopted in 1985, and great advancements have been made in both river forecasting technology and gaging throughout the basin since its adoption. The purpose of the WMOP was to assess alternatives to current regulating criteria set forth in the WCM. The final study will be provided to USACE should a subsequent revision to the WCM be pursued.

The Technical Team identified several objectives of this study including maximizing water supply, reducing flood risk, and enhancing environmental flows in the Truckee River. Furthermore, the Technical Team also had the goal of developing flood control regulations that would be implementable in real time operations and flexible to advancements in technology in the future. The MOEA provided a holistic technical framework that allowed the Technical Team to accomplish these goals.

This paper documents the utilization of the MOEA in the WMOP Study and how it allowed for the analysis of flexible regulation criteria and the balancing of basin objectives in developing proposed revisions to the WCM. This paper will begin by providing a brief overview of the MOEA framework. Next, the paper discusses the methodology behind the analysis of the study. This includes details of how the Baseline Scenario was modelled, how the study employed FIRO to determine flood space requirements, and how the MOEA was applied to the WMOP Study. Lastly, the paper will provide a brief discussion of the results of the MOEA and how the Technical Team utilized the output of the MOEA to assess alternatives to flood control regulation criteria prescribed by the WCM.

Truckee River Basin Overview

The Truckee River Basin has a combination of five Federal reservoirs (Lake Tahoe, Martis Creek Reservoir, Boca Reservoir, Stampede Reservoir, and Prosser Creek Reservoir) and two private reservoirs (Donner Lake and Independence Lake) that reside upstream in California (see Figure 1). These reservoirs are operated for flood control and to meet a combination of municipal, industrial, agricultural, environmental, and recreational demands. The 2015 Truckee River Operating Agreement (TROA) also allows a variety of basin stakeholders to store water in the reservoirs so improvements to the WCM, which was not updated when TROA was implemented, have potential to benefit a wide variety of interests.

The Truckee River flows from these reservoirs in California 120 miles downstream to its terminus Pyramid Lake (Rieker, 2010). The river crosses the California/Nevada border near Floriston, California and it flows through the Truckee Meadows and Reno, Nevada, where water is removed from the river through a variety of municipal and agricultural diversions. This region represents areas of major development in the basin, and the WCM defines operational flow targets in Reno that were developed specifically to protect this region and downstream from flooding.

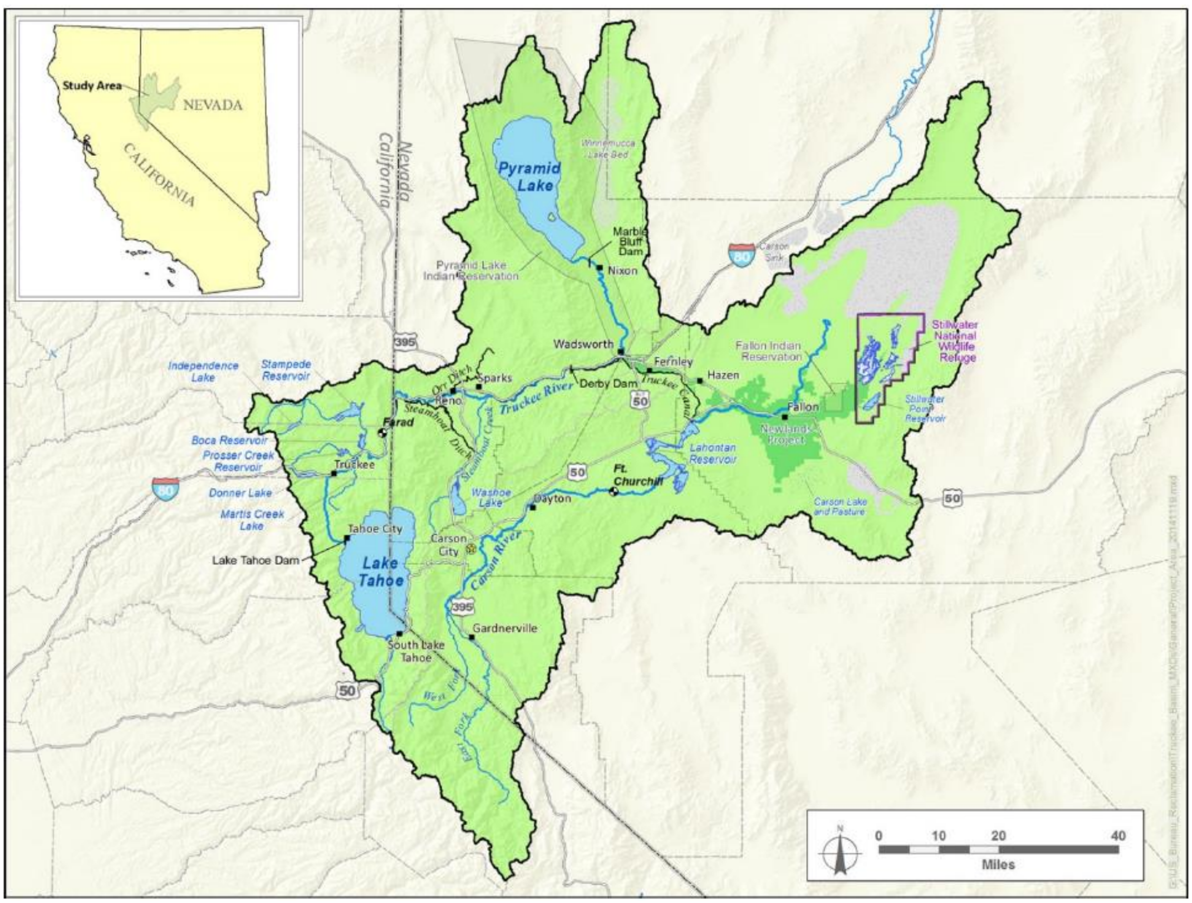

Figure 1. Map of the Truckee River Basin (U.S. Department of Interior, Bureau of Reclamation, 2015).

MOEA Overview

Multi-Objective Evolutionary Algorithms (MOEAs) are non-linear, stochastic optimization methods that can be used to identify the best compromise solutions along a path of potential policy alternatives given a set of defined objectives and decision variables. MOEA provides an intelligent, systematic process for developing a solution that balances the achievement of multiple (often competing) objectives. It provides users with quantitative information to use when evaluating tradeoffs (Reed et al., 2013).

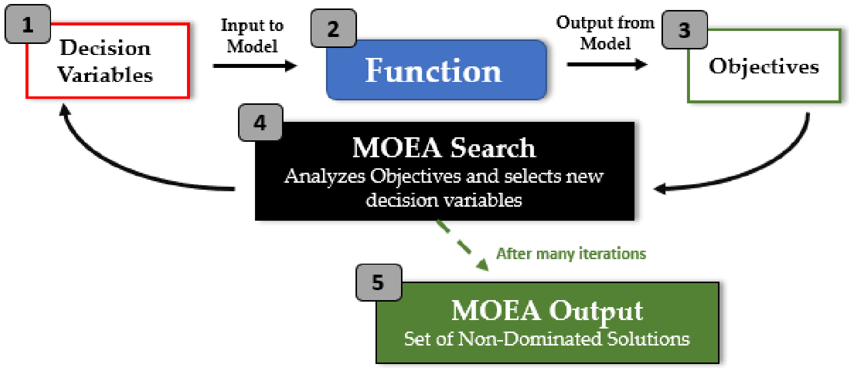

Figure 2. Interactions between the five main components of the MOEA

Figure 2 provides a schematic summarizing the five main components of the MOEA and the interactions between them. Central to MOEA is the ***function***, or an equation (simpler)/model (more complex) that is undergoing optimization. ***Decision variables***, which represent the parameters that the MOEA will optimize, are input to the function by the MOEA. ***Objectives*** are output from the function and represent the performance of the function given an input set of decision variables. As the MOEA runs, the ***MOEA Search Algorithm*** intelligently selects new sets of decision variables to evaluate in the function by learning the relationship between decision variables and objective performances. The process of evaluating the function's objective performances with new sets of decision variables is repeated many times until the MOEA converges on a solution.

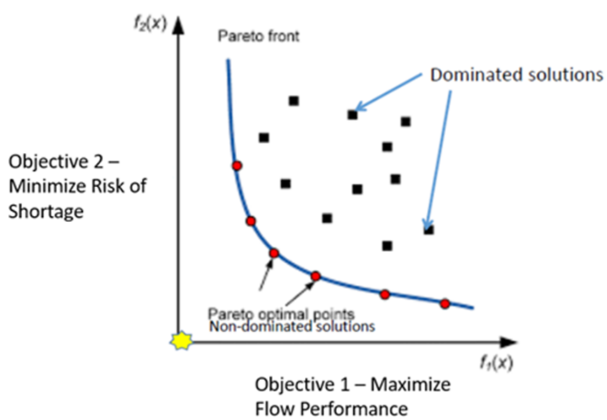

Figure 3. Illustration of two-dimensional Pareto-Front and Non-Dominated vs. Dominated Solutions (adapted from CADSWES, 2019)

Due to the multi-objective nature of the optimization analysis, there is often a competing nature between different objectives (i.e., what is good for one objective is not always good for other objectives). Thus, the output from the MOEA, or optimal results, are not single solutions, but are instead represented by sets of "nondominated solutions" (also called "Pareto optimal points"). A ***nondominated solution*** is a solution that provides an optimal trade-off between objectives, in that no objective can be further improved without harming another objective. In contrast, a ***dominated solution*** is a solution where one of the objectives can be improved without harming any of the other objectives (i.e., there is no trade-off to improve that objective), and thus, is not an optimal trade-off point. The collection of nondominated solutions is often referred to as the ***Pareto front***. These concepts are illustrated in Figure 3 for a conceptual two objective (i.e., two-dimensional) problem where the objectives are to minimize both the x and y values. From this set of nondominated solutions, the "optimal solution" is determined through a more subjective analysis of the tradeoffs between objectives.

Methodology

This section discusses the methodology of how the alternative policies in the WMOP Study were modelled. The section begins with an overview of the Baseline Scenario of the study. Next, this section provides an overview of the "By a Model" Method (the application of FIRO to determine flood space requirements). Lastly, a discussion is provided on how the MOEA Framework was applied in the WMOP Study to model flood control regulating criteria alternatives.

Baseline Scenario

The Baseline Scenario in the WMOP Study was developed to model the Truckee River Basin under contemporary policy. This scenario utilized two RiverWare© models: the *TROA Planning Model* (Planning Model) and the *TR Hourly River Model* (Hourly Model). The Planning Model runs at a daily timestep, and its purpose in the Baseline Scenario is to provide modelling results necessary to quantify water supply and environmental objectives. The Hourly Model runs at an hourly timestep, and its purpose is to provide modelling information necessary to quantify the study's flood damage mitigation objective. These models run in tandem where the TROA Planning model determines the daily water supply and storage implications of a scenario, and the TR Hourly Model determines the shorter-term flow routing implications. To consider flood scenarios larger than those found in the historical dataset, the study data set also routed a series of scaled hindcast events where historical precipitation forcings were scaled to produce the 100-yr, 200-yr and 500-yr recurrence interval flood hydrographs.

"By a Model" Method: Using FIRO to Determine Flood Space Requirements

One of the major goals of the WMOP Study was to develop flood control regulation criteria that would be flexible and adaptable to future advances in technology. In the context of the WMOP a methodology named the "By a Model" Method was developed to utilize probabilistic inflow forecasts provided by the National Weather Service California Nevada River Forecast Center (CNRFC) to make more efficient determinations of flood space requirements. This method was designed so that any future advances in forecasting technology would seamlessly integrate into the determination of increasingly efficient and intelligent flood space requirements.

The following sections document the "By a Model" Method. This includes a summary of the method's input data requirements and structure. Furthermore, the method's algorithm is described in detail. This includes an example of how flood space requirements are derived from a forecast while balancing the accuracy of a forecast with acceptable levels of risk.

Data Requirements

CNRFC regularly produces ensemble forecasts of river flows for locations within the California/Nevada region utilizing their Ensemble Streamflow Prediction (ESP) technology. These ***forecasts*** are composed of 41 traces or "potential futures" of river flows at a particular location. To produce the traces, ESP technology utilizes a rainfall-runoff model that is initialized with current soil and snow conditions. This model is run with an ensemble of climate data which each trace being based in-part on climate from a historical year. The short-term outlooks are driven by short-term weather forecasts, then the traces blend into historical meteorology for the respective year as the weather forecast skill decreases. The ensemble of traces contained within a forecast allow computation of the risk/probability that the forecasted runoff will be within specified ranges.

As input to the "By a Model" Method in the WMOP Study, CNRFC developed a dataset of daily ***hindcasts***, or "re-forecasts", of history for several locations within the Truckee River Basin. Hindcasts are like forecasts, but they represent what the forecasts *would have been* in history utilizing current ESP technology. While hindcasts and forecasts are similar, it is important to draw a distinction between the two. Forecasts apply current modeling technology to predict future flows that have not yet occurred, whereas hindcasts are forecasts produced with current ESP technology for periods of time that have already occurred.[1] In specific, CNRFC provided daily hindcasts for the period spanning water years 1990 to 2020. Additional hindcasts were provided for February and March of 1986. The data availability of the hindcasts determined the period of record for the study. This set of hindcasts provided the ability to assess the relationship between forecasting skill and acceptable risk in determining flood space requirements in the Truckee Basin Federal reservoirs. This relationship and how it was balanced in the "By a Model" Method is detailed in the following sections.

The Relationship Between Risk and Skill

Fundamentally, ensemble forecasts (or hindcasts) are more accurate at shorter outlooks than longer outlooks, and the level of acceptable risk associated with flood information contained in a forecast should relate inversely to the outlook and accuracy of a forecast (Gwynn, 2022b). For example, if a large rain event is forecasted to occur at a 1-day outlook, there is a strong meteorologic signal that this event is highly likely to occur. The "By a Model" Method should respond to the accuracy in this forecast of the storm at a 1-day outlook by operating more conservatively and requiring sufficient flood space to mitigate impacts of the coming storm. If a similar rain event is forecasted at a 14-day outlook, this event could occur, but it is less certain to occur than in the case of the 1-day outlook, also there is additional time to evacuate flood space in the intervening days while the forecast becomes more certain. The flood space requirements determined by the "By a Model" Method are designed to respond to the reduction in skill of hindcasts with outlook. The method is engineered to allow this relationship to be optimized. That is, using the large dataset of hindcasts provided by CNRFC, the optimal relationship between hindcast skill and acceptable level of risk can be explored to develop flood control regulation criterion that will adequately protect against the storms.

Volume Over Target Calculations

The goal of flood control operations in the Truckee Basin is to maintain appropriate space in reservoirs to be able to store sufficient inflow to the basin to protect against downstream flooding. The goal of flood control operations of reservoirs is to store basin inflows that would otherwise cause the downstream Reno Gage to exceed a target of 6,500 cfs (otherwise known as the Flood Target Flow).[2] This concept is reflected in the fundamental equation in "By a Model" Method to determine flood space:

$$RFS = \sum_{t=0}^{t_f} \max\left(I_t - T_{downstream\ target\ flow}, 0\right)_{\mathrm{high}\ flows} * \text{Flow to Volume Conversion} \tag{1}$$

In this equation, RFS is the required flood space in units of acre-feet, $\boldsymbol{I_t}$ is the hindcasted Reno unregulated flow at time t, $\boldsymbol{T_{downstream\ target\ flow}}$ is the Flood Target Flow at Reno (6,500 cfs), and $\boldsymbol{t_f}$ is a given outlook (i.e., 10 days). This is like the method applied to determine the seasonal flood space requirement which utilizes this equation on seasonal historical inflows; the "By a Model" method applies the equation to ESP forecasts (Gwynn, 2022a).

[1] Other differences between hindcasts and forecasts exist but are not relevant to the scope of this paper.
[2] The target flow at the Reno Gage is under review, and this is a preliminary number that was chosen to be used in the study.

As discussed above, there is a tradeoff between the collective accuracy of hindcasts versus the acceptable level of risk. To account for this, the “By a Model” Method assesses flood risk at varying outlooks by computing the volume of flood space that would be exceeded by a specified percentage of traces. This “exceedance percentage” is the percent of traces for which the flood space would be insufficient to store the inflows should that trace occur and is thus an estimate of the risk of filling all the flood space associated with having a specified volume of flood space. Note that this is an estimate of the risk associated with having sufficient flood space as the hindcasts (and all models and meteorological forecasts that they are based on) may have biases and inaccuracies based on the current state of the science. The percentage used can vary by outlook and be adjusted to meet the study objectives. To facilitate this computation, Equation 1 is applied to all traces of a hindcast at multiple outlooks. To provide a simple example, assume a hindcast for a given day is composed of ten traces. Equation 1 is applied to each trace of this hindcast at outlooks of 1, 2, 5, 7 and 14 days resulting in the Cumulative Storage over the Flood Target Flow summarized by Table 1. Note, implementation of the “By a Model” Method in the WMOP Study included outlooks up to 365 days to incorporate runoff information contained in forecasting into the methodology.

Table 1. Example of applying the Cumulative Storage over Flood Flow Target calculation to a hindcast

		Outlook (days)				
		1-Day	**2-Day**	**5-Day**	**7-Day**	**14-Day**
Unregulated Inflow Volume over Flood Target Flow (acre-feet)	**Trace 1**	0	0	5,000	15,000	15,000
	Trace 2	0	1,000	4,000	10,000	11,000
	Trace 3	100	1,500	3,000	12,000	12,000
	Trace 4	0	0	2,000	12,500	12,700
	Trace 5	0	0	2,000	12,500	12,500
	Trace 6	0	200	3,000	11,500	11,500
	Trace 7	50	100	1,000	10,000	10,000
	Trace 8	500	2,000	5,000	6,000	7,000
	Trace 9	0	500	1,500	11,500	11,500
	Trace 10	0	0	0	10,000	11,000

Exceedance vs. Outlook Curve: Balancing Hindcast Skill with Risk

The risk assessment portion of the “By a Model” Method summarizes the results of the “Cumulative Volume over the Target Calculation” to a single, refined flood space requirement by selecting the cumulative volume at a specified exceedance percentage for each outlook that best meets the study objectives. These exceedance percentages are characterized by an “Exceedance Outlook” relationship to facilitate efficient optimization. The required exceedance then varies as a function of the outlook in a well-defined manner. The parameterization of this exceedance-outlook curve is optimized by the MOEA to meet the study objectives. This defines how conservative the refined flood space requirement should be to give the desired improvements in storage available to water supply while ensuring that sufficient flood space is reserved to mitigate downstream flooding (i.e., meeting the study objectives). Figure 4 provides an example of a prototype Exceedance vs. Outlook Curve. This curve defines that at a 1-day outlook, the 0% exceedance of the hindcasted 1-day Cumulative Storage over Flood Target Flow should be used in the determination of the flood space requirement. In other words, at a 1-day outlook, the most conservative (i.e., largest) forecasted volume for flood space requirements should be considered. In contrast, at the 14-day outlook, the 60% exceedance of the hindcasted 14-day Cumulative Storage over Flood Target Flow should be considered in the determination of the flood space requirement. Intuitively, because there is less skill in and more time to reach a 14-day outlook than a 1-day outlook, a less conservative volume of flood space requirements is appropriate by this Exceedance vs. Outlook relationship.

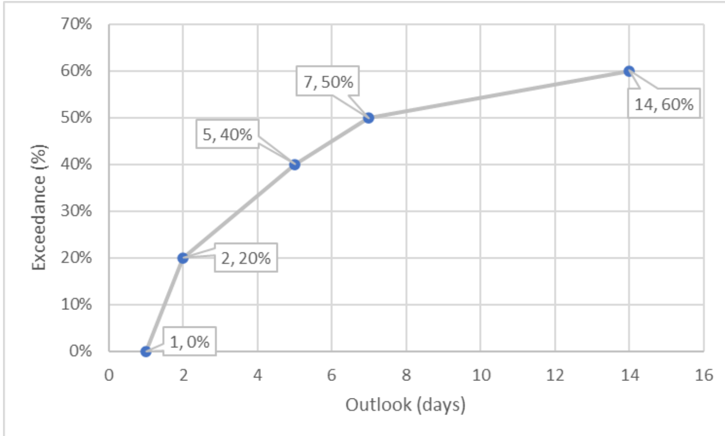

Figure 4. Example Exceedance vs. Outlook Relationship

Applying the Exceedance vs. Outlook curve from Figure 4 to the Cumulative Storage over Flood Target Flow values for the example hindcast (see Table 1) results in values for required flood space by outlook shown in Table 2. The "By a Model" Method selects the required flood space for this hindcast based on the most conservative value defined by the Exceedance vs. Outlook curve. For example, this is associated with the required flood space calculated for the 7-day outlook of 11,500 acre-feet.

Table 2. Required Flood Space calculations by outlook and risk, and the required flood space as calculated by the "By a Model" Method for the example hindcast

Outlook	1-Day	2-Day	5-Day	7-Day	14-Day	"By a Model" Method Required Flood Space
Exceedance	0%	20%	40%	50%	60%	
Required Flood Space by Outlook (acre-feet)	500	1,100	3,000	11,500	11,300	**11,500**

The last step of the "By a Model" Method adds a factor of safety in the "By a Model" Method and is like the "Modified Hybrid EFO model" recommended in a similar project on the Russian River (Jasperse et al., 2020). As a part of the WMOP Study, updated guide curves, known as Revised Guide Curves, for required flood space were developed using updated historical datasets and updated methods (Gwynn, 2022a). The "By a Model" Method applies a minimum value to the required flood space calculation determined by the Exceedance Vs. Outlook curve as a percentage of the Revised Guide Curve to maintain. That is, the required flood space, as calculated by the "By a Model" Method, will always be at least as large as a percentage of the flood space from the Revised Guide Curve. How this percentage is determined is discussed in the proceeding section. The following equation represents this interaction between the percentage of the Revised Guide Curve to maintain and the calculations for required flood space as determined by the hindcast data and the Exceedance vs. Outlook curve:

$$RFS_{Final} = Max[\%\ Revised\ Guide\ Curve\ to\ Maintain\ , RFS_1, RFS_2, RFS_5, RFS_7, RFS_{14}, \ldots] \qquad (2)$$

In this equation, RFS_{Final} represents the final required flood space as determined by the "By a Model" Method and RFS_n represents the required flood space calculated utilizing the Exceedance vs. Outlook relationship at an n day outlook.

Parameterization of the Exceedance vs. Outlook Relationship

As described above, the Exceedance vs. Outlook relationship is designed to determine a flood space requirement from an RFC Ensemble.

To accomplish this, the Exceedance vs. Outlook relationship was parameterized by the following equation:

$$Exceedance = C + A(Outlook)^B \tag{3}$$

A, B, and C in Equation 3 are coefficients characterizing the shape of the exceedance outlook curve. By constraining the B coefficient to values greater than zero, the resulting exceedance percentage will be increasing as a function of outlook. Thus, for smaller outlooks, more conservative flood space requirements should be implemented, in contrast to longer outlooks, whose forecasted flood space requirements are more uncertain, and therefore should not require highly conservative flood space requirements long in advance of their materialization.

In total, the “By a Model” Method required four parameters (see Table 3). The MOEA optimized each of these parameters through analysis of what configuration best met objectives related to water supply, flood risk mitigation, and environmental flows.

Table 3. Parameters required by the “By a Model” Method

	Decision Variables
"By a Model" Method	Exceedance Coefficient A
	Exceedance Coefficient B
	Exceedance Coefficient C
	Percentage of Revised Guide Curve to Maintain

Modelling Alternatives using MOEA

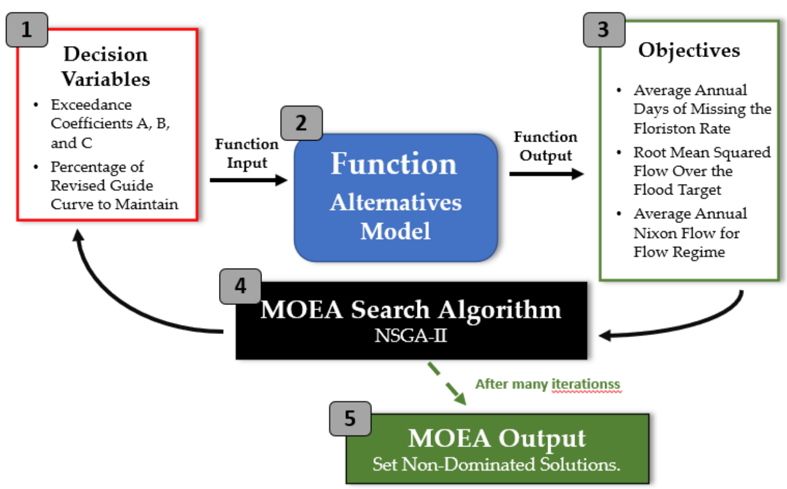

Figure 5. Schematic summarizing the configuration of MOEA Components in the WMOP Study

This section describes how the MOEA was set up in the WMOP Study. Figure 5 provides a high-level schematic that summarizes the configuration of each MOEA component. The proceeding sections describe the configurations in detail. Refer to MOEA Overview for more generic descriptions of MOEA components and the interactions between them.

MOEA Function in the WMOP Study

The MOEA Function in the WMOP Study was configured to utilize the Alternative Model, an identical modelling framework to the Baseline Scenario (see Baseline Scenario) except for a few key changes limited to those necessary to allow for alternative flood control regulating criteria to be modelled. Among these changes was implementing the "By a Model" Method for determining flood space requirements into the Planning Model as opposed calculating flood space requirements via methodology prescribed in the current WCM.

MOEA Objectives in the WMOP Study

The objectives in the WMOP Study can be summarized as water supply, flood risk mitigation, and environmental flows objectives.[3] To evaluate model performance, calculations were developed for each objective of the WMOP Study. The MOEA required that the result of the calculation for each objective was a single number that accurately represented an objective's performance for an entire model run. Table 4 summarizes the names of objective calculations developed for the three main objectives in the study.

Table 4. Summary of the main objective calculations in the WMOP Study.

Objective	Calculation Name
Water Supply	Average Annual Volume for Floriston Rate
Flood Risk Mitigation	Root Mean Squared Flow Over the Flood Target
Environmental Flows	Average Annual Volume for Flow Regime

MOEA Decision Variables in the WMOP Study

The decision variables utilized in the MOEA of the WMOP Study included the four parameters associated with the "By a Model" Method for determining flood space. Refer to Table 3 for a list of these parameters.

MOEA Search Algorithm in the WMOP Study

The evolutionary algorithm employed in the MOEA of the WMOP Study was the Non-dominated Sorting Genetic Algorithm II (NSGA-II). The Technical Team selected this algorithm for two primary reasons:

(1) It is well-established and has been found to be successful and dependable in civil engineering applications.
(2) It was technically feasible to implement.
(3) It provided run-time efficiency by supporting function evaluations in parallel.

For more documentation on NSGA-II, refer to the referenced paper *Multi-Objective Evolutionary Algorithm (MOEA) Tool Utilization and Development* (Precision Water Resources Engineering, 2022).

MOEA Output in the WMOP Study

The output of the MOEA in the WMOP Study was configured to be 150 non-dominated solutions. This set of solutions represented the space of optimal solutions determined by the MOEA. From this set of 150 non-dominated solutions, the Technical Team would deliberate on the tradeoffs between objectives in the study and ultimately select the set of decision variables associated with the "By a Model" Method that would represent the optimal flood control regulating criterion that balanced the tradeoff between water supply, flood risk mitigation, and environmental flow objectives in the study.

[3] Note, there were more than 3 objectives for the MOEA in the WMOP Study. For the sake of simplicity, the objectives discussed in this paper are limited to three of the main objectives.

The proceeding sections discuss the results of the MOEA and how the Technical Team determined the optimal flood control regulating criteria utilizing its results.

MOEA Results Overview

The MOEA evaluated the Alternative Model 3,000 times, and once completed, it output a set of 150 non-dominated solutions (referred to as MOEA Scenarios). The results discussion of the MOEA is divided into two sections. The first provides an overview of the potential benefits to stakeholder objectives represented in the MOEA Scenarios. The second provides a discussion on the observed tradeoffs between the objectives.

Potential Benefits to Stakeholder Objectives

Table 5 provides a comparison between the objective performances of Baseline Scenario and the best performing MOEA Scenario for each objective. In this table, smaller values signify better objective scores.

Table 5. Comparison of objective performances between Baseline Scenario and the best performing MOEA Scenario for each objective

	Average Annual Volume for Floriston Rate (acre-feet)	Average Annual Volume for Flow Regime (acre-feet)	RMS Flow over Flood Target (cfs)
Baseline Scenario	-263,079	-148,066	162,530
Best MOEA Scenario Performance	-263,379	-149,075	140,987
Difference (Improvement)	-300	-1009	-21,543

The Average Annual Volume for Flow Regime objective showed a 1,009 acre-feet improvement in the best performing MOEA Scenario over the Baseline Scenario for this objective. This is equivalent to an additional 37,000 acre-feet of storage being available in the 37-year model run of the MOEA Scenario to meet environmental flow targets over the Baseline Scenario. Similarly, yet to a lesser extent, the maximum improvement shown by MOEA Scenarios over the Baseline for the Average Annual Volume for Floriston objective was 300 acre-feet. Equivalently, the best performing MOEA Scenario shows an additional 11,100 acre-feet of water available to meet the Floriston Rate Target over the 37-year model run.

The benefits for both objectives were realized in the modelling in a select few years in the of the period. For example, of the 37,000 acre-feet of additional storage available to meet environmental targets in the 37-year model run, over 15,000 acre-feet was accumulated in water year 2011. This additional storage persisted in the system until the drought year of 2015 when it was used to meet environmental flow targets for almost two additional months (see Figure 6).

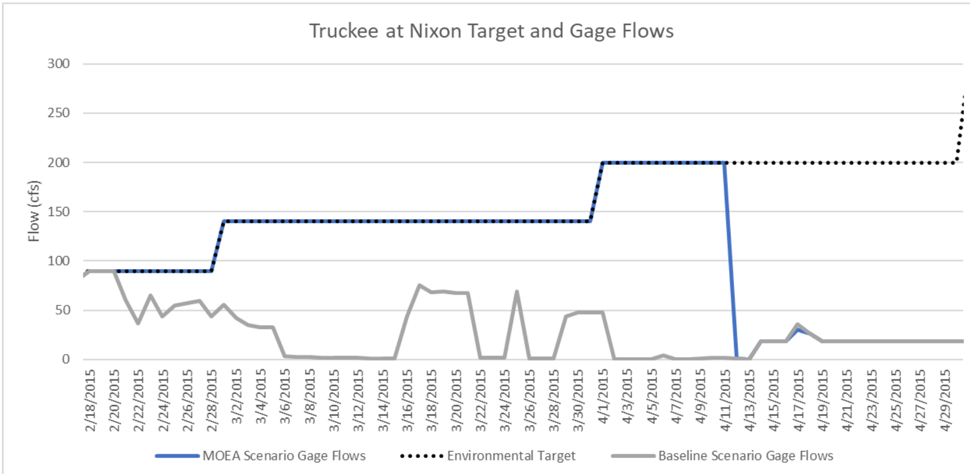

Figure 6. Example environmental benefits of the best performing MOEA Scenario over the Baseline Scenario

The maximum improvement shown by the non-dominated solutions over the Baseline Scenario for the RMS Flow over Flood Target objective is 21,543 cubic feet per second (cfs). The best performing non-dominated solution for this objective represented significant flood risk mitigation, particularly in reducing peaks flows of flood events and the amount of time the flows at the Reno Gage were above the Flood Target Flow of 6,500 cfs.

Tradeoffs Between Study Objectives

Figure 7 and Figure 8 **Error! Reference source not found.**illustrate the tradeoffs between objectives by comparing objective scores for MOEA Scenarios against one another. The 2-dimensional Pareto Front between these two objectives has been estimated in these plots by the red line. As depicted by these two plots, there exists a well-defined tradeoff between both the environmental and water supply objectives with the flood damage's objective. While this behavior was anticipated, the MOEA provided a way to quantify these tradeoffs which aided in the selection process.

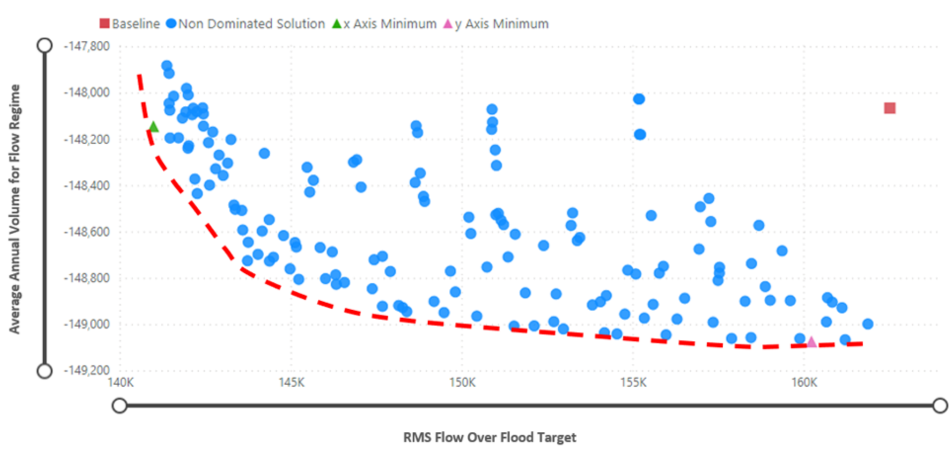

Figure 7. Non-dominated solution objective performances from the MOEA and Baseline Scenario Run for the Average Annual Volume for Flow Regime (i.e., environmental objective) and RMS Flow over Flood Target (i.e., flood objective) objectives. The Pareto Front between the two objectives is estimated by the red dashed line.

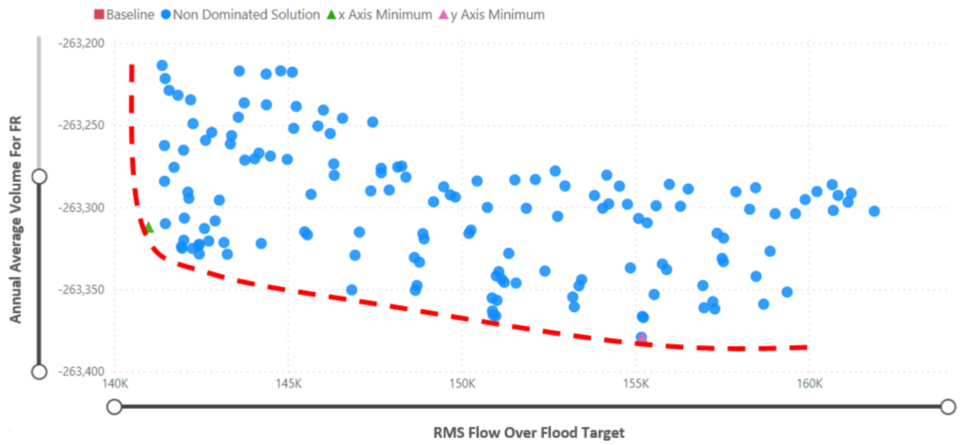

Figure 8. Non-dominated solution objective performances from the MOEA and Baseline Scenario Run for the Average Annual Volume for Floriston Rate (i.e., water supply objective) and RMS Flow over the Flood Target (i.e., flood objective) objectives. The Pareto Front between the two objectives is estimated by the red dashed line.

Overview of Selecting the Optimal Alternative

The Technical Team needed to select one preferred alternative utilizing the 150 MOEA Scenarios provided by the MOEA. This process was completed in three phases that allowed for efficient elimination of several less desirable MOEA Scenarios such that stakeholders could focus detailed analysis and discussion on a curated, short list of "best" MOEA Scenarios from which to pick one. The following subsections document these three phases and provide a summary of how the best MOEA Scenario influenced the preferred alternative of the WMOP Study.

Initial Filtering of MOEA Scenarios Using Parallel Axis Plots

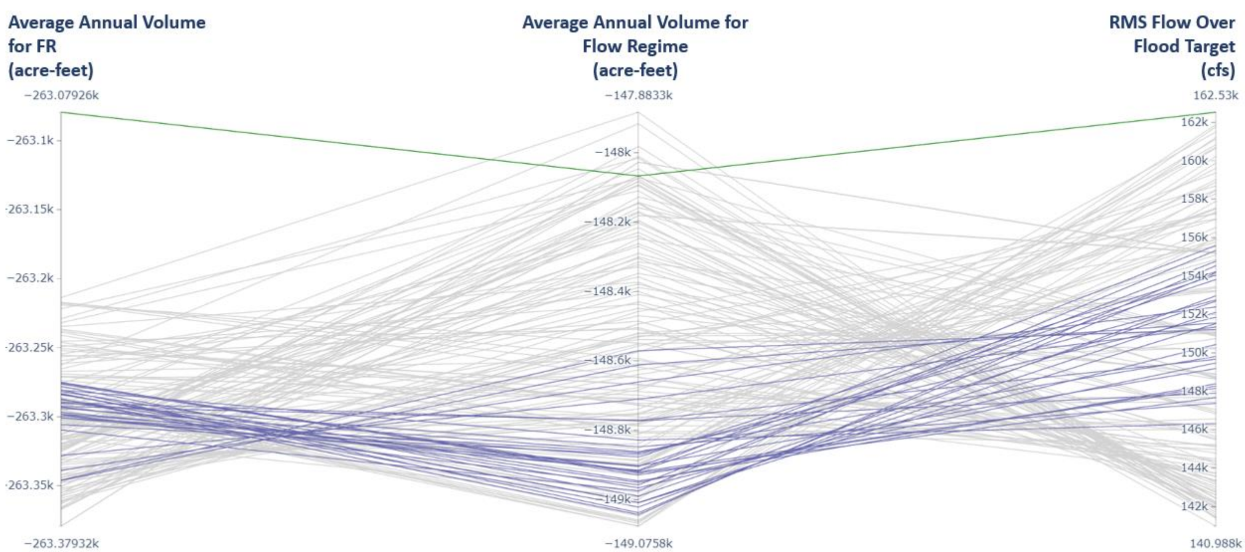

Figure 9. Parallel Axis Plot of objectives performances of non-dominated solutions (blue and light grey) and the Baseline Scenario (Green) for the three objectives. Scenarios that remained after initial filtering are colored grey.

The goal of phase one of the selection process was to filter down the MOEA Scenarios as much as possible from a high-level view of their performances. The Parallel Axis Plot, shown in Figure 9, offered an efficient means by which to accomplish this. Each line in this plot that connects and crosses the vertical axes, referred to as scenario lines, represents either non-dominated solutions (colored light grey or blue on the plot) or the Baseline Scenario (colored green on the plot). The vertical axes each represent an objective in the MOEA, and performance is indicated by where the scenario lines cross an objective's axis. The plot is oriented so that down on a vertical axis is always a better score for that objective.

The blue lines on the Parallel Axis Plot represent the MOEA Scenarios that were selected by the Technical Team during Phase 1 of the selection process. These were selected by removing the scenarios that performed poorly for any objective while trying to keep some of the best performing scenarios for each objective. All scenarios that were selected as a part of the first phase of the selection process performed better than the Baseline Scenario for each of the objectives.

Additional Stakeholder Screenings of MOEA Scenarios

The second phase of the analysis involved a more detailed review of the remaining 30 MOEA Scenarios displayed in Figure 9 to determine the top four best MOEA Scenarios. During this phase, each agency represented in the Technical Team was required to determine their 20 best MOEA Scenarios evaluating their own subjective decision criteria for what represented "acceptable" and "better" tradeoffs between the study objectives. Afterward, a small committee consisting of at least one representative from each agency met to determine the best MOEA Scenarios agreed upon by all cost share partners. The four scenarios selected by this committee are summarized in **Table 6**.

Table 6. Summary of the performances of the four MOEA Scenarios selected by the small committee during the second phase of the selection process.

Model Name	Annual Average Volume For FR (acre-feet)	Average Annual Volume For Flow Regime (acre-feet)	RMS Flow Over Flood Target (acre-feet)
A	-263,287.08	-149,020.48	152,978.25
B	-263,293.83	-148,860.67	149,820.18
C	-263,298.24	-148,956.60	154,776.49
D	-263,287.18	-149,042.15	154,546.62

Selecting the Preferred MOEA Scenario

After agreeing upon the top 4 MOEA Scenarios, the Technical Team met at the WMOP Select Preferred Alternative Workshop in March of 2023 to conduct an in-depth review of time series results associated with each the four remaining MOEA Scenarios to determine the best performing scenario. Ultimately, the Technical Team selected C as the best performing MOEA Scenario for the following three reasons.

Central to the decision-making process at the workshop were stakeholder concerns with fluctuations in flood control capacity observed in the MOEA Scenarios. Figure 10 provides an example of these fluctuations by depicting simulated results of Prosser Creek Reservoir Flood Control Capacity for the four MOEA Scenarios and the Baseline Scenario in 2017, a very wet year. The simulated results show that it was not uncommon to see large spikes in Prosser Flood Space Requirements in 2017. The "spikiness" shown in MOEA Scenarios in Figure 10 are caused by short lead times of storms in the forecast. Storms typically do not show up weeks in advance in the forecasts; rather, their lead time in the forecasts is much shorter, sometimes on the order of days. As a result, flood space requirements determined by the "By a Model" Method react quickly and dramatically to the changes in forecasts that occur at shorter lead times.

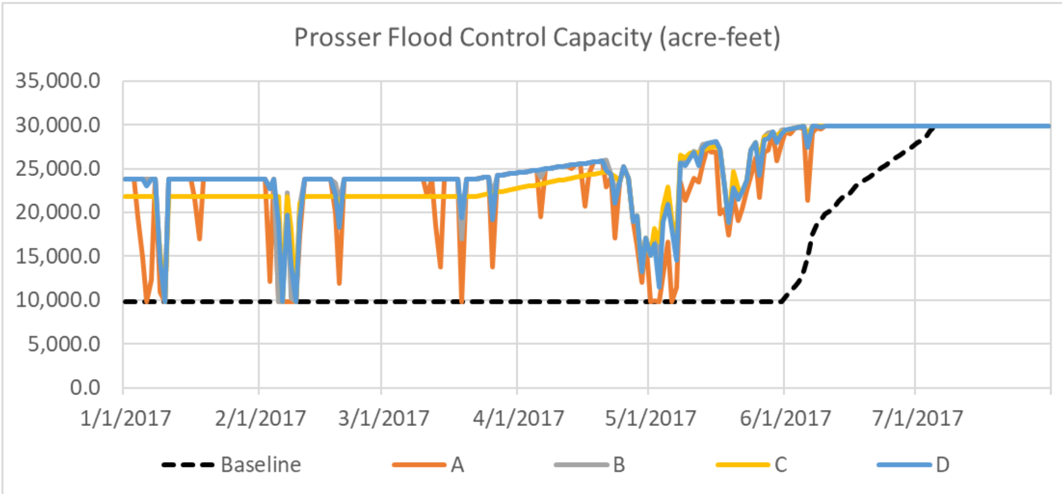

Figure 10. Prosser Flood Control Capacity for the Baseline and top four MOEA Scenarios during runoff of 2017.

A major concern with these fluctuations was its impact on fish species in the Truckee River. For example, if one of these fluctuations in flood control capacity on Prosser Creek Reservoir occurred on a day when the reservoir was close to full, strict adherence to regulation criteria would force Prosser Creek Reservoir operators to evacuate its flood storage immediately, and the reservoir would begin evacuating water at an exceedingly high rate. These types of fluctuations in river flows would have negative impacts on fish species in the river.
The Technical Team determined MOEA Scenario C to be a better scenario than the other MOEA Scenarios because it showed the least amount of fluctuation in flood space requirements and, therefore, variability in river flows.

Table 7. Simulated peak flow at the Reno Gage for the January 1997 100-year Scaled Flood Event.

Scenario	Baseline	A	B	C	D
Peak Reno Gage Flow (cfs)	19,215.4	17,507.3	15,245.3	15,245.3	17,507.3

A second observation that further substantiated C as the best performing MOEA Scenario was its performance in a simulated January of 1997 100-year Scaled flood event. MOEA Scenarios B and C reduced the simulated peak flows at the Reno Gage for this event by over 4,000 cfs (see Table 7). According to the stakeholder flooding expert, these differences in peak flow represent the difference between flooding a large industrial park in the region and introducing chemical contamination into the river. Note, while MOEA Scenario B showed similar benefit in reducing peak flows for this event, it was eliminated from consideration due to inferior performance for other basin objectives outside the scope of this paper. The third and final observation that led to C being selected was that it the best among the four scenarios at the water supply objective (Annual Average Volume for FR).

Overview of the Preferred Study Alternative

One of the goals of the WMOP was to develop flood control operational criteria that not only improved the stakeholder objectives in the basin but was also operationally feasible to implement. While the Technical Team did arrive at a final preferred MOEA Scenario, concerns about the feasibility of implementing the scenario, specifically in relation to issues surrounding fluctuations in flood space requirements discussed previously, prevented this scenario from becoming the preferred alternative for the study. Namely, two concerns were raised with the fluctuation issue in addition to environmental concerns. The first was how "feasible" it would be to physically make the release changes called for by the "By a Model" Method during a real flood event. Second, reservoir operators in the basin were concerned with liability of operating to fluctuating forecasts because it could result in situations where:

1. Operators may be forced to needlessly spill stakeholder water downstream.
2. Operators may not have evacuated enough flood space to protect against a flood event.

As a result, the Technical Team developed the preferred alternative for the study as a slight modification to MOEA Scenario C. The modification was designed to (1) leverage the benefits to environmental flows and water supply of using the "By a Model" Method, and (2) smooth over fluctuations in the required flood space to avoid negative impacts of flow variability. The results from the preferred alternative are still being developed and, therefore, excluded from this report.

Conclusion

The Technical Team of the WMOP successfully collaborated to develop an alternative flood control regulation criterion that leverages the information contained within ensemble forecasts to maximize water supply and enhance environmental flows while protecting against floods in the Truckee Basin. While issues lead times of storm events in the ensemble forecasts manifested, at times, in large fluctuations of forecasts during wet periods, methodologies were set in place to allow for the regulation criterion to be flexible and adapt with future advancements in forecasting technology. The MOEA provided the necessary technical infrastructure from which to leverage the skill in ensemble forecasts to meet stakeholder objectives more effectively. The technical effort completed as a part of the WMOP will result in a proposed revision of the USACE WCM for the Truckee River Basin.

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