Multi-Objective Optimization of Folsom Reservoir Operation

By

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ABSTRACT

Contemporary reservoir systems often require operators to meet a variety of objectives, which frequently complicate water management decisions. In addition, many reservoir objectives have non-linear relationships and are difficult to implement using traditional optimization techniques. A practical application of multi-objective optimization is developed for Folsom Reservoir near Sacramento, California where water delivery, hydropower and downstream temperature control are desired. In the summer and early fall fishery habitat is managed by regulating river temperatures downstream of Folsom reservoir. Downstream temperature is adjusted by the volume and location of release from the reservoir. However, temperature management can impose a cost to hydropower generation if colder temperature water bypasses the hydropower turbines. The objectives are to minimize delivery target deviation, minimize downstream temperature target exceedance, and maximize hydropower generation. In this application, optimal seasonal reservoir release decisions are found using a multi-objective evolutionary algorithm and a one-dimensional hydrodynamic reservoir temperature model. Seasonal reservoir release policies, June through November, from two scenarios are examined to evaluate tradeoffs between objectives. Results suggest alternate release strategies to minimize costs to water delivery, temperature target exceedance, and hydropower generation. Model sensitivity, limitations and recommendations for future development are also discussed.

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1. INTRODUCTION

The United States has over 6,390 large reservoirs, many which are designated as multi-purpose systems operating for hydropower generation, irrigation, water supply and flood control. Because multi-purpose reservoirs serve more than one use and uses often conflict, they must frequently compromise each individual objective. Multi-objective reservoir systems often perform more poorly than anticipated, due to the complexity of operating such systems with conflicting purposes (World Commission on Dams, 2000).

California has a complex surface water supply system which includes 20 state and federal reservoirs. California's federal storage projects have a variety of officially recognized purposes including: river regulation, navigation, flood control, irrigation and domestic use, fish and wildlife mitigation, protection and restoration, power and fish and wildlife enhancement (U.S. Bureau of Reclamation, 2004). To emphasize the economic importance of this system, in the year 2000, the state as a whole used 42.2 billion cubic meters (BCM) of water supplies for farming and agriculture, 11 BCM for urban water use, and 48.6 BCM for environmental purposes (California Department of Water Resources, 2005). As a result, in part or whole, California is the largest agricultural producer in the nation, the most populous, and the most popular travel destination in the United States (California Department of Water Resources, 2005). Also in the year 2000, California's federal reservoir systems generated over 6 billion kWh of hydroelectric power (Linenberger, 2002). Average total hydropower generation accounts for nearly a quarter of the power in the state. In addition, environmental resources related to riparian and wetland areas such as bird watching, fishing, hunting or other wildlife recreation in California is a hundreds of millions of dollars a year industry (California Department of Water Resources, 2005).

Many of Californias large reservoirs are multi-purpose systems which include environmental habitat protection. For example, hydropower operations on river systems can impose stressful temperature conditions for some species of fish. In other regions of the west, sustaining Fall-run Chinook salmon in the long-term is thought to require modifying river and reservoir temperatures to maintain a suitable thermal regime (Sauter et al., 2001). Likewise in California, temperature control devices have been added to allow reservoir operators to blend releases from various depths to provide temperatures that better support a habitat for targeted fish and fish hatcheries (U.S. Bureau of Reclamation, 2004). This exemplifies the increase in the complexity of reservoir operation due to conflicting reservoir purposes in California's reservoir systems.

Although more reservoir purposes make broader use of available resources, they increase the decision making burden on reservoir operators and exacerbate suboptimal reservoir operations. Greater attention and understanding of conflicting water demands between anthropogenic and environmental systems increase the importance and motivation of efficient water system operations (Wik, 1995; Howitt and Lund, 1999). Numerous investigations have examined methods to optimize reservoir policy decisions (Labadie, 2004; Yeh, 1985). Recently, non-traditional optimization methods, such as genetic algorithms, have gained popularity with multi-objective problems to overcome hindrances of traditional methods (Deb, 2001).

This thesis presents an application of multi-objective genetic algorithm optimization techniques with a one-dimensional hydrodynamic reservoir temperature model to find better temperature dependent reservoir release policies. The optimization is designed for a single reservoir with multiple objectives and is applied to Folsom Reservoir near Sacramento, California. The purpose of this work is to find a set of optimal solutions and tradeoffs among water supply release quantities, reservoir release temperature and the quantity of hydropower generation. This paper investigates previous research and application of water quality and optimization modeling followed by details of Folsom Reservoir and its operation. Simulation and optimization model formulations, application, and results also are presented. Finally, the thesis discusses the analysis of the model application, conclusions and recommendations for further study.

1.1 Previous Water Quality Modeling and Optimization

Past water quality and optimization modeling methods are examined for technique, efficiency, and limitations for application to Folsom Reservoir. Previous research and application have focused on classical methods, joining water quality with systems planning and analysis to seek efficient reservoir operation. Although reservoir infrastructure improvements increase efficiency, additional reservoir objectives increase the difficulty of reservoir operation. Studies examine various water quality parameters and solution techniques for optimal reservoir operation. Traditional optimizations of reservoir water quality operation use linear programming techniques to include dissolved oxygen and biochemical oxygen demand control (Loucks and Jacoby, 1972) or reliability programming (chance-constraint) for salinity control (Orlob and Simonovic, 1982).

A pioneer of water quality and water quantity optimization includes a study by Loftis et al. (1985) that explores optimal reservoir release for a system of two lakes, one affected by mine drainage. This study demonstrated a method to identify optimal quality while meeting quantity constraints by deciding reservoir releases from varied vertical depths to simulate selective withdrawal ports from the reservoir outlet structure. Typically, water quality and optimization models of the reservoir system are separated and iteratively solved for, as is this study.

Other researchers have investigated similar water quality and water quantity optimization using a variety of solution techniques and applications. A similar inspection of water quality and water quantity optimization is in the Murray-Darling basin in Australia. Dandy and Crawley (1992) developed a linear optimization model to allocate water releases to minimize salinity impacts downstream. Related research includes regional water distribution system optimization and includes reservoirs using water quality objectives. Mehrez et al., (1992) focus is on real-time operations rather than planning scenarios for service to agricultural and urban users. A network optimization was used to allocate water in the distribution system from a variety of sources (surface and groundwater) to meet water quality requirements of the recipient at minimal cost. The objective is to minimize daily operational costs (desalination, dilution with higher quality water, etc.) by modeling hourly operations for a 24 hour period. Hayes et al. (1998) examined improving water quality downstream from hydroelectric power plants in the Cumberland River basin of Virginia and Tennessee. Poor reservoir water quality (dissolved oxygen and temperature) frequently affects river reaches downstream of chains of sequential reservoirs. A combined water quantity and quality network algorithm generated optimized hydroelectric and water quality release policies by maximizing the hydroelectric benefits and minimizing the water quality penalties. Detailed operational, flood space, power generation and quality constraints describe the network system. Thus far, studies have addressed quantity and quality, but not uncertainty. An investigation by de Azevedo et al. (2000) presents a study for river basin planning and incorporates hydraulic and physical properties, chemical properties, boundary conditions and sink/source uncertainties. The study in the Piracicaba River basin in Brazil incorporates a multi-reservoir optimization (using a linear network solver) and water quality routing simulation for wastewater discharge, agricultural, municipal and industrial uses. An ensemble of Monte Carlo realizations was used to evaluate the uncertainty.

These optimization schemes are commonly hampered by computational limitations, compromised objective functions, and inefficient solution schemes (Deb, 2001). Traditional optimization assumptions also can impose undesired decisions and results. Single optimal solutions require either "an accept or reject" response, often caused by optimization techniques that inherently oblige the analyst to make decisions a priori (Cohon, 1978). Table 1.1 provides a list of multi-objective optimization classifications and their respective solutions and techniques based on information presented in Cohon (1978), Deb (2001), Miettinen (1999) and Collette and Siarry (2003). Desired optimization techniques provide a set of solutions, relieve the analyst from decision making, and provide the decision maker a variety of better-performing alternatives.

As previously described, many multiple objective optimizations are solved with compromising procedures due to limitations in solution methods. Although most practical problems are multi-objective, it is common for problems to be solved with traditional methods which are altered single objective optimization solution methods (Deb, 2001). Some limitations of traditional approaches as summarized by Deb, 2001:

1. Only one Pareto-optimal solution can be expected to be found in one simulation run of a classical algorithm.

2. Not all Pareto-optimal solutions can be found by some algorithms in non-convex multi-objective optimization problems.

3. All algorithms require some problem knowledge, such as suitable weights or target values.

Table 1.1: Types of Multi-Objective Optimization Classifications

Classification	**Flow of Decision Information**	**Solution Technique**	**Optimal Solution**
No-Preference	No information from Decision Maker	Method of Global Criterion; Multi-objective Proximal Bundle	Single solution
A Posteriori	Analyst to Decision Maker	Weighting Method; $\varepsilon-$Constraint; Hybrid; Weighted Metrics; Achievement Scalarizing Function Approach	Range of solutions (set)
A Priori	Decision Maker to Analyst	Value Function Method; Lexicographic Ordering; Goal Programming	Range of solutions (set)
Interactive	Iterative (Analyst to Decision Maker to Analyst to Decision Maker etc.)	Interactive Surrogate Worth Trade-Off; Geoffrion-Dyer-Feinberg; Sequential Proxy Optimization; Tchebycheff; Step; Reference Point; GUESS; Satisficing Trade-Off; Light Beam Search; Reference Direction Approach; NIMBUS; Others	Single solution

Source: Cohon (1978), Deb (2001), Miettinen (1999), and Collette and Siarry (2003).

Multi-objective evolutionary algorithms are particularly well suited for problems that are non-linear and where traditional methods would require impractical computation time. Common issues to practical multi-objective water quality optimization problems include (Dorn and Ranjithan, 2003):

1. Multiple conflicting objectives,

2. Need for efficient solution algorithms to reduce simulation runs,

3. Techniques that can manage non-linear solution space, and

4. Accurate tradeoff results.

Other common difficulties using classical multi-objective optimization methods include (Deb, 2001):

1. Initial solution influences convergence to optimal solution,

2. Search mechanisms that get "trapped" in local optima,
3. Non-robust optimization algorithms,
4. Inefficient discrete search space techniques, and
5. Inefficient use of parallel machine configuration.

These limitations suggest using alternative methods to solve multi-objective optimization problems that avoid compromising the integrity of the objectives and provide the desired optimal solution set.

Water resources and optimization studies using alternative optimization techniques is a relatively new and growing field of research. Water resources optimization applications can be solved by alternative techniques such as swarm-based (honey-bee mating) (Haddad et al., 2006) or other heuristic approaches such as ant colony optimization algorithms (Jalali et al., 2007). A technique called evolutionary or genetic optimization for multi-objective and non-linear problems also circumvents traditional optimization limitations. John Holland first conceived of evolutionary algorithms (EA) in 1975 and David Shaffer completed the first application in 1984. In 1989 David Goldberg's book on multi-objective evolutionary algorithms (MOEA) popularized the technique and as a result, the early to mid 1990s were an active pursuit of MOEA research (Deb, 2001).

Evolutionary algorithms stem from the idea that optimal solutions can be found by evolving a population of solutions in a Darwinian manner. Thomas Bäck (1996) explains that "evolutionary algorithms are a class of direct, probabilistic search and optimization algorithms gleaned from the model of organic evolution." In general, a numerical evolutionary algorithm for multi-objective problems consists of a random population of solutions that mate, reproduce and discourage poor solutions in successive generations, with each generation of solutions converging on the Pareto optimal front.

Evolutionary algorithms also can address non-linear search spaces. For example, groundwater monitoring or remediation applications are well suited to multi-objective evolutionary optimizations because they can involve many parties with conflicting components as well as a non-linear search space. Reed and Devireddy (2004) investigate a solution to groundwater monitoring for a polluted aquifer using a NSGA-II algorithm. Others such as Cedeño and Vemuri (1996) find optimal remediation of a contaminated aquifer using the groundwater model SUTRA and a multi-niche crowding algorithm.

Water pollution and control is also a theme in surface water optimization applications. Multi-objective genetic algorithms have been used to evaluate watershed growth and water quality where urban land use and pollution were competing objectives. Dorn and Ranjithan (2003) used a two objective genetic optimization algorithm (NSGA-II) and a one-dimensional stream channel, fate and transport water quality model. This investigation found how land use could be changed while still maintaining a desired level of water quality and was further researched by Bekele and Nicklow (2005). A similar study in the Tseng-Weng river basin in Taiwan used three objectives (using two sub-models) to maximize constituent assimilative capacity of the river, minimize treatment cost and maximize the river flow for recreational purposes (Chen and Chang, 1998). Multi-objective genetic evolutionary algorithm techniques that improve the solution and computational speed are highly desired for water resources problems. Reed and Devireddy (2004) report an increase in simulation efficiency by using e-dominance archiving and automatic parameterization techniques.

Algorithms listed in Tables 1.2 and 1.3 identify non-elite and elite multi-objective evolutionary programs based on information presented in Deb (2001). Evolutionary algorithm evaluations by Zitzler et al. (2001) suggest Strength Pareto Evolutionary Algorithm 2 (SPEA2) (Zitzler et al., 2001) and the Non-dominated Sorted Genetic Algorithm II (NSGA-II) (Deb et al., 2002) out perform other algorithms yielding the most accurate results. Dorn and Ranjithan (2003) also found that the NSGA-II was more efficient than a Hybrid GA/local search algorithm by an order of magnitude. NSGA-II also was insensitive to a random seed selection and small population pools (Dorn and Ranjithan, 2003). Preliminary results indicate that NSGA using elitism and SPEA perform comparably, the advantage being the elitism technique (Zitzler et al., 2001).

Table 1.2: Non-Elitist Multi-Objective Evolutionary Algorithms

Abbreviation	**Non-Elitist Multi-Objective Evolutionary Algorithms**
VEGA	Vector Evaluated Genetic Algorithm
VOES	Vector-Optimized Evolution Strategy
WBGA	Weight-Based Genetic Algorithm
-	Random Weighted Genetic Algorithm
-	Multiple Objective Genetic Algorithm
NSGA	Non-Dominated Sorting Genetic Algorithm
NPGA	Niched-Pareto Genetic Algorithm
-	Predator-Prey Evolution Strategy

Source: Deb (2001).

Table 1.3: Elitist Multi-Objective Evolutionary Algorithms

Abbreviation	**Elitist Multi-Objective Evolutionary Algorithms**
-	Rudolph's Elitist Multi-Objective Evolutionary Algorithm
NSGA-II	Elitist Non-Dominated Sorting Genetic Algorithm
DPGA	Distance-Based Pareto Genetic Algorithm
SPEA (2)	Strength Pareto Evolutionary Algorithm
TDGA	Thermodynamical Genetic Algorithm
PAES	Pareto-Archived Evolution Strategy
-	Multi-Objective Messy Genetic Algorithm

Source: Deb (2001).

2. FOLSOM RESERVOIR

In the foothills of California's Sierra Nevada range, at the base of the American River watershed (4,908 km^2), is Folsom Reservoir (as shown in Figure 2.1). The major tributaries, North and South Forks of the American River, supply water to the reservoir year round. Holding back the 1.2 billion m3 capacity reservoir is the main dam, a 427 m (1,400 ft) long gravity dam constructed of concrete, with earth embankments on either side. Lake Natoma located 11 river km (7 miles) downstream from Folsom Reservoir functions as a single reservoir that re-regulates Folsom Reservoir hydropower releases and supplies water to the Nimbus Fish Hatchery (U.S. Bureau of Reclamation, 2004). Further downstream past the City of Sacramento, the American River confluences with the Sacramento River and flows through California's Central Valley to the Sacramento-San Joaquin Delta. Prior to the confluence, at river km 15 (mile 9.4), is the Watt Avenue Bridge landmark along the American River and is an important location for temperature regulation discussed later in the report.

Nearly 40% of the runoff received by Folsom reservoir is snowmelt which usually peaks in April or May (U.S. Bureau of Reclamation, 2004). Observations at nearby weather stations (from Sacramento Executive Airport) provide an insight to the climate which significantly influences reservoir conditions (Table 2.1) (NOAA National Climatic Data Center, 2005). The trends reveal hot, clear, sunny, and dry conditions in the summer months while the winter months are cooler, cloudier, and wetter.

Although development throughout modern history along the American River and riparian corridor has disturbed aquatic habitat and fisheries, they remain an integral part of the local ecosystem. Two species, the Central Valley Steelhead (*Oncorhynchus mykiss*) and the Fall-run Chinook salmon (*Oncorhynchus tschawytscha*) are important fishery populations on the American River. Sensitive periods for these fish species are times of reproduction, egg incubation and juvenile rearing. Adult Steelhead arrive to spawn late fall to spring. Juvenile Steelhead reside in the lower American River for a year or more before migrating to the ocean between late winter and early summer. The Nimbus Fish Hatchery is also essential to sustaining this species; Steelhead counts of returning adults indicate that nearly all originated from the facility (U.S. Bureau of Reclamation, 2004b). Similarly, Fall-run Chinook salmon spawn and rear juveniles. However, as observed on the Columbia River, the Chinook are particularly sensitive to temperature (Sauter et al., 2001). On the American River, late October or early November begins typical spawning and incubation periods for the salmon (Reclamation, 2004).

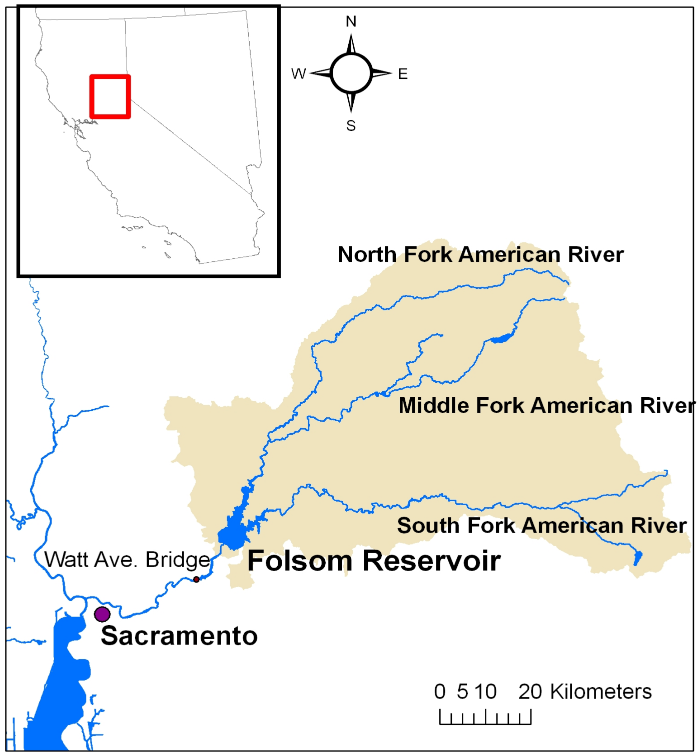

Figure 2.1: Area Map of the American River Watershed and Folsom Reservoir

2.1 History of Folsom Reservoir

The City of Sacramento, situated just south of the lower American River and east of the Sacramento River, is in an area where topography and sedimentation from hydraulic mining contributed to frequent flooding. Sacramento's early permanent structures were inundated frequently as far back as the 1850's. The creation of the Reclamation and Swampland Act of 1861, the Green Act of 1868, and motions for valley-wide flood control planning in the 1880's attest to early attempts to tame and control floodwaters (Hundley, 2001). Other early interests on the American River, particularly industry, appeared in the early 1860's. Horatio Gates Livermore conceived and built the original Folsom Dam and power canal in 1893 to support his logging business. His sons carried on their father's legacy and constructed the first electric powered saw mill in the United States. Later the Livermore brothers and the General Electric Company built the longest hydroelectric high voltage transmission line in the world (at the time), in 1895, from Folsom to Sacramento (Linenberger, 2002).

Table 2.1: Mean Observed Climate Data for Sacramento Executive Airport, California

Month	**Clear Days (Mean)**	**Sunshine (As a % of possible days)**	**Daily Max. temp. 32.2°C or higher (Mean)**	**Ave. wind speed (km/hr)**	**Ave. Relative Humidity (Morn and After)**	**Precip. 0.25 mm or more (Mean no. of days)**
No. of Years	*49*	*46*	*55*	*55*	*19*	*66*
Jan	7	48	0	11.1	91/71	10
Feb	8	65	0	11.7	89/61	9
Mar	10	74	0	13.5	86/52	9
Apr	12	82	*	13.8	83/44	5
May	17	90	5	14.4	83/38	3
Jun	22	94	12	15.4	78/32	1
Jul	27	97	22	14.3	77/30	*
Aug	26	96	19	13.5	78/29	*
Sep	24	93	13	11.9	77/31	1
Oct	19	86	3	10.3	80/37	3
Nov	10	66	0	9.7	87/56	7
Dec	8	49	0	10.3	89/68	9
Annual	188	78	74	12.6	83/46	58

Note: An asterick (*) indicates a vaule greater than zero, but less than 0.5.
Source: NOAA National Climatic Data Center (2005).

At the turn of the twentieth century, California's water resource requirements were identified and quantified. Edward Hyatt, State Engineer, devised the California "Central Valley Plan" amidst the Great Depression of the 1930's and a severe drought in California from 1929 to 1935. The plan called for hydroelectric power generation and fresh water to repel saline waters from the Sacramento-San Joaquin Delta area. The plan was designed to benefit agriculture, urban and industrial users and to create jobs for the unemployed. In 1933 the Central Valley Project Act became a federal project, due to unsuccessful financing by the state (Hundley, 2001).

Nearly a century after the first planned flood protection for the region, the United States Army Corps of Engineers completed construction of Folsom dam and reservoir in 1956. The primary purpose of the facility was to alleviate flood damages to the Sacramento area. By the 1950's the Sacramento area was a major center for agriculture, industry and urban settlement and had water demands on the reservoir much greater than flood control. Ultimately, operation of Folsom Reservoir became the responsibility of the United States Bureau of Reclamation (Reclamation) and by default an integral part of the California Central Valley Project (CVP) serving water supply to both agricultural and urban users (Reclamation, 2004).

Stream channel obstructions, habitat degradation and over fishing are common reasons given for California's declining anadromous fishery populations (Hartman et al., 2000). In response to greater concerns for declining anadromous fish populations in California and on the American River, the Nimbus Fish Hatchery was authorized and built in 1955 downstream from Folsom Reservoir. Despite efforts to maintain sustainable fishery populations, two American River fish populations continued to dwindle; the Central Valley Steelhead a threatened species at the federal level and a species of "special concern" at the state level and the Fall-run Chinook salmon (a candidate of the endangered species list) (USFWS, 2003). The Endangered Species Act (ESA) of 1978, one of the strictest regulatory protection laws for endangered and threatened species, provides enforceable habitat protection by fishery management agencies. The ESA also protects quantity and quality of water to aquatic populations including temperature of water in the lower American River (Reclamation, 2004).

At present, increasing numbers of reservoir operators must respond to new requirements and multiple objectives (WCD, 2000). Reclamation operates Folsom Reservoir to "provide conservation of water in the American River for flood control, fish and wildlife protection, recreation, protection of the [Sacramento-San Joaquin] Delta from intrusion of saline ocean water, irrigation, and [municipal and industrial] water supplies, and hydroelectric power generation" (Reclamation, 2004). Although complex and conflicting objectives are necessary to maintain a balance of the natural resources used in the American River watershed or other areas, they create a challenge for efficient reservoir operation.

2.2 Folsom Reservoir Operations

The timing, quality and quantity of releases from Folsom Reservoir are influenced both locally and as far away as the Sacramento-San Joaquin Delta. A total of approximately 0.6165 BCM (billion cubic meters) (500 TAF) of water per year is drawn from Folsom Reservoir to meet water demands in the CVP system (Reclamation, 2005). Local water demands on the lower American River are subject to contracts and water right requirements of urban and agricultural users in nearby Sacramento and neighboring areas. The "Water Forum" established by interested parties within the American River watershed, specify demands on the system given specific hydrologic conditions (California Department of Water Resources, 2005). Regulatory requirements such as the State Water Resources Control Board (SWRCB) Decision 839 and the federal Central Valley Project Improvement Act (CVPIA) Section 3406 (b)(2), specify minimum allowable flows in the lower American River. Water sports and facilities at Folsom Reservoir, downstream at Lake Natoma, and on the lower American River also are present. Recreation at these facilities depends on reservoir water levels and flows for activities such as boating, rafting, and fishing (Reclamation, 2004). More geographically distant policy regulations like the revised SWRCB Decision 1641 specify Sacramento-San Joaquin Delta water quality and could require Folsom Reservoir to release water to meet these requirements (SWRCB, 2000).

Two seasons dominate the operation of Folsom Reservoir, the wet season from October to May and the dry season from June through September. The highest annual storage volume occurs in the spring months where rainfall and snowmelt inflows are high and reservoir releases are low. Increasing reservoir releases and thermal stratification begin in late May and early June. Increased solar radiation and low-volume warm inflow in the summer could cause the epilimnion to reach temperatures of 21°C. Metalimnion and hypolimnion temperatures typically range between 12°C – 21°C and 9°C – 11°C respectively. Empirical evidence show warmer summer inflows minimally mix with the hypolimnion thermal layer (Yaworsky, 2005). In summer, the "cold pool" storage is most affected by diffusion of heat from warmer stratification layers.

Folsom Dam has three general outlet structure types: hydropower penstock, spillway gates, and flood outlet works (Table 2.2). The Folsom power plant can generate a maximum of 215 MW from three penstocks by releasing a total of approximately 245 m^3/sec (Reclamation, 2004). Each penstock tower has some flexibility of opening shutters at different elevations as indicated in Figure 2.2, known as the temperature control device (TCD) which became fully functional in 2004. These outlets, controlled by reservoir operators, can blend water from varying temperatures. Spillway gates at the top of the dam structure are used to prevent water from overtopping the reservoir or can release warm water from the top of the reservoir to conserve cooler water for later in the year. Eight flood outlet works are also located lower in the dam structure. Flood outlets have a total release of up to approximately 900 m^3/sec. The flood outlet works are typically used when an imminent reservoir flooding threat is present, but also can be used for temperature control by releasing cooler water from deeper locations within the reservoir.

Table 2.2: Folsom Dam Outlet Information

<table>
<tr><th>Quantity</th><th>Outlet Location</th><th>Elevation (m msl)</th><th>Approximate Maximum Flow Rate (m^3/s)</th></tr>
<tr><td>8</td><td>Spillway Radial Gates</td><td>127</td><td>16,000</td></tr>
<tr><td rowspan="4">3</td><td>Penstock, All Shutters Closed</td><td>122</td><td rowspan="4">245</td></tr>
<tr><td>Penstock, Upper Shutters Open</td><td>111</td></tr>
<tr><td>Penstock, Middle Shutters Open</td><td>103</td></tr>
<tr><td>Penstock, Lower Shutters Open</td><td>87</td></tr>
<tr><td>4</td><td>Upper (Tier) River Flood Outlets</td><td>84</td><td>457</td></tr>
<tr><td>4</td><td>Lower (Tier) River Flood Outlets</td><td>64</td><td>457</td></tr>
</table>

Folsom Reservoir operators reserve releases from the reservoir for irrigation, urban demands, and hydroelectric power during the dry season. However, riparian

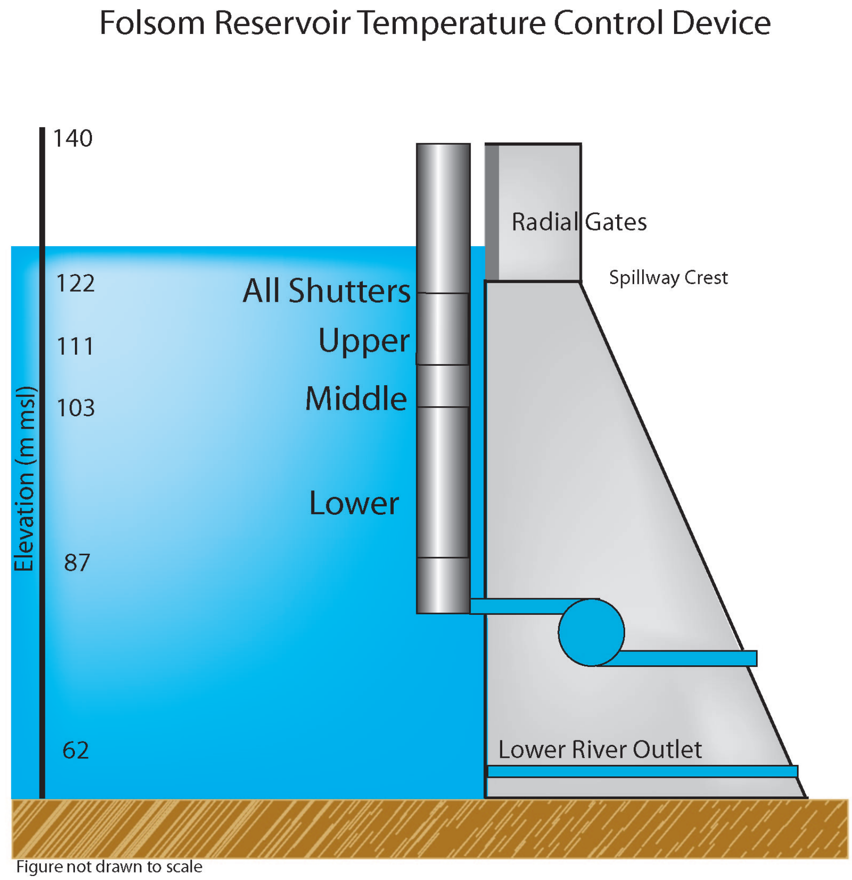

Figure 2.2: Folsom Reservoir Outlets and Temperature Control Device Schematic

and fish hatchery habitat uses are sensitive to water temperature during the same period, the early summer through fall. Reclamations operation criterion specifies that within available resources and capabilities, they will meet objectives set by NOAA Fisheries and target a daily average temperature of 18.3°C (65°F) . This temperature target is 31.2 km downstream of the reservoir between Nimbus Dam and the Watt Avenue Bridge and is in effect June 1 to November 30 (Reclamation, 2004). The temperature objective is to protect endangered fisheries and the rearing of juvenile steelhead from temperature related stress and predators (Reclamation, 2004b). Management consideration also is given to the reservoir "cold water pool" to use later in the year for fall-run Chinook salmon. Between November and December reservoir release temperature management is usually no longer needed because the lake mixes and thermally de-stratifies. This annual event coincides with the months of cooler air temperatures and the lowest storage volumes (the result of summer supply use and preparation for winter precipitation and flooding) (Washburn, 2005).

During the wet season the reservoir is managed to operate within flood control levels determined by the United States Army Corps of Engineers (USACE) and the Sacramento Flood Control Agency (SAFCO) (Reclamation, 2004). Flood control constraints are not imposed June through November. However, in the fall, Folsom Reservoir is targeted for 0.43 billion m^3 of storage in preparation for winter floods (Washburn, 2005).

3. FOLSOM RESERVOIR MANAGEMENT DECISIONS

Past investigations of Folsom Reservoir focus on optimal power generation and optimal multi-reservoir and multi-use operation (Mariño and Mohammadi, 1983; Mohammadi and Mariño, 1984; Mohammadi and Mariño, 1984a). These and additional challenges exist for Folsom reservoir operators. Operators determine the release policies for hydropower generation, water supply delivery and manage for periods of temperature dependent environmental releases. Optimally, the desired temperature water is sent through the penstock to generate hydropower as well. In June, Reclamation reservoir operators prepare the summer through fall release strategy. Current reservoir operation is planned using expert judgment and trial and error modeling to supply water demands and meet fishery requirements for the temperature control period through the fall. These proposed release strategies are reviewed at monthly meetings by Reclamation operators, temperature modeling experts, fisheries biologists and interested community members (Yaworsky, 2005). Adjustments to the release schedule are made and updated monthly to factor in biological conditions.

In early summer, Reclamation operators prepare for temperature management through the fall knowing a few initial conditions. Initial conditions known in June are: (1) reservoir storage volume and (2) the reservoir temperature profile. Uncertain parameters are inflow and outflow volumes, meteorological conditions, inflow temperatures, and reservoir release withdrawal configurations (Reclamation, 2004b). Estimated parameters, such as inflows and water demands are forecasted monthly for an annual period and are updated each month by Reclamation (Reclamation, 2004).

An actual operation is discussed below to illustrate reservoir release configurations. The initial condition of Folsom Reservoir for June 2001, a dry year, was an elevation of 135 m msl and a storage volume of 858 million m^3 (for comparison, June 2005, a wetter year, had an elevation of 142 m msl and 1.18 BCM of storage). The temperature control device at Folsom Reservoir allows for the adjustment of release elevations to the hydropower penstocks and attempts to manage the temperature downstream of the reservoir. Reclamation's operators initially released water from the upper-most penstock configuration (see middle graphic in Figure 3.1). This pulled water from the upper portion of the reservoir for release downstream. As anticipated, summer solar radiation increased the temperature in the reservoir (top graphic in Figure 3.1) and by mid-July the upper inlets were closed and the middle level of the penstocks were used to pull water from a lower elevation in the reservoir. At the end of August a mixed release configuration was used to blend water from the middle and lower penstock inlets. The penstock inlets were re-configured once more in mid-September to manage release temperatures using the lower penstock openings. The last dry season operational configuration was in early November where hydropower generation was bypassed and the lower river outlet was used to send cooler water downstream.

Daily minimum and maximum temperatures recorded at Watt Avenue Bridge are illustrated in the lower graphic in Figure 3.1. As is shown in this example, the daily maximum and minimum temperatures at Watt Avenue Bridge exceeded the temperature target of 18.3°C. Lower reservoir storage and warmer conditions seem likely to have contributed to this outcome. The operation change at the lower river outlet in early November released water from lower in reservoir and had a significant effect on stream temperature at the Watt Avenue Bridge.

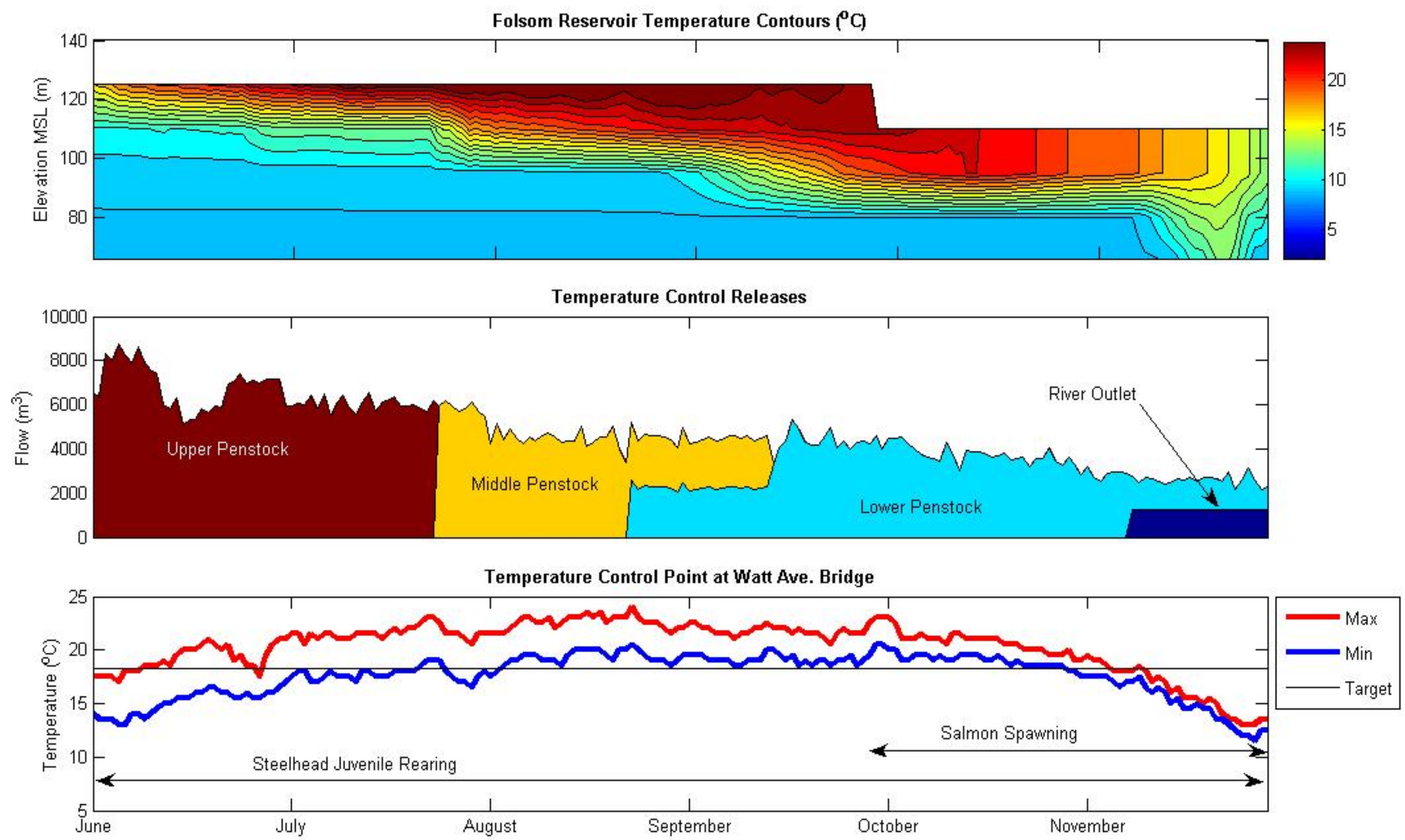

Figure 3.1: Historical Folsom Reservoir Temperature Contours, Release Operations and Downstream Temperatures at Watt Avenue Bridge June 1, 2001 to November 30, 2001

4. MODEL FORMULATION AND DEVELOPMENT

Two separate modeling components were configured and integrated to find and analyze reservoir release decisions to meet three specific objectives. First, a water quality model simulates and predicts water temperature within the reservoir. The second model is a reservoir operations optimization routine which searches for an optimal set of reservoir release solutions to best fulfill the combination of the three objectives: water supply delivery, hydropower generation and downstream temperature control. The formulation and development of each model is described below.

4.1 Dynamic Lake Model (DLM)

Reservoir water temperature is estimated by simulating lake dynamics given prescribed release quantities and release depths. The UC Davis Dynamic Lake Model (DLM), a one-dimensional hydrodynamic simulation with vertically distributed temperature and water quality parameters, is used to estimate water temperatures of lakes or reservoirs. This model also features advanced reservoir inflow dynamics that improve the plunging and intrusion of inflows into the reservoir (Fleenor, 2001).

DLM simulates reservoir temperature profiles using stream inflows, meteorological inputs, such as solar, wind, air temperature and precipitation, and reservoir releases from specified depths at the dam outlets. The temperature model is organized with dynamically adjusted vertical Lagrangian layers. Parameterized processes such as heat, mass and momentum fluxes and mixing are linked to the layer structure. Specific discussions of the DLM assumptions and physical processes are available in Fleenor, 2001, Fleenor, 2005 and Imberger and Paterson, 1981. Both spatial and time discretizations are dynamically adjusted to suit the systems response to changes as small as 3 centimeters and as short as 15 minutes. The default output time step is daily and layers are dynamically separated or joined as required during the simulation. Simulation results reveal reservoir temperature contours through time or daily temperature profiles.

General assumptions of the DLM model were investigated and found acceptable for application to Folsom Reservoir. ArcMap©Geographic Information System (GIS) was used to determine the spatial dimensions of the reservoir and upstream inflow components, as shown in Figure 4.1. The reservoir body is represented as a uniform plan-view rectangular area (6.1 km long by 5.5 km wide) with eight sub-units describing both the North and South Forks of the American River flowing into Folsom Reservoir.

Five outlet locations were implemented in the model. The upper-most outlet delivers water to the penstock for hydropower generation without blending water

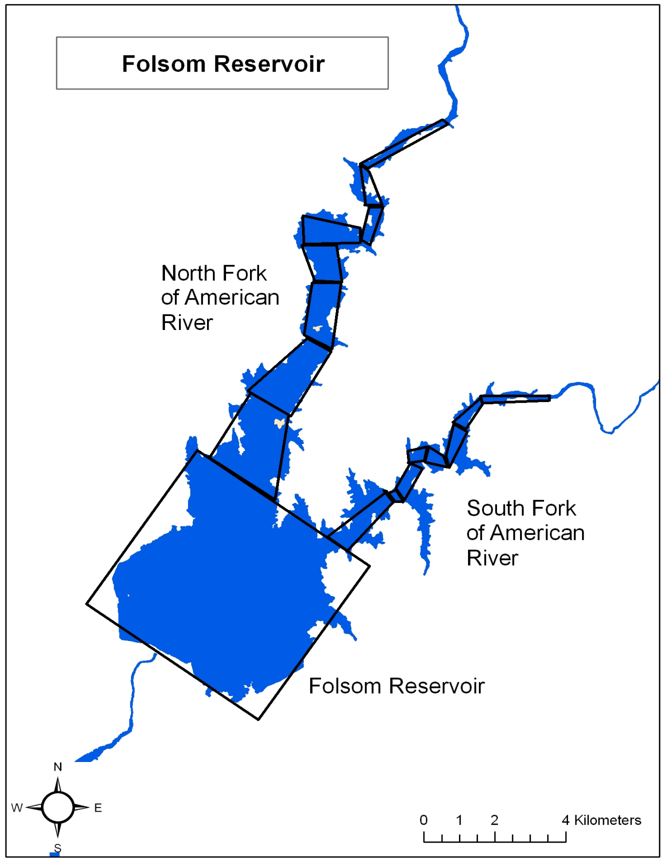

Figure 4.1: Folsom Reservoir and Plan View of DLM Configuration

from lower elevations. Next, three outlets represent the upper, middle and lower temperature control device inlets to the penstock and a fifth outlet represents the low elevation river outlet which bypasses hydropower generation. Inflow temperature, inflow and outflow, climatic, and cloud cover data were retrieved from the Bureau of Reclamation (Reclamation), California Data Exchange Center (CDEC), California Irrigation Management Information System (CIMIS) and the National Weather Service (NWS) respectively. Physical and biological model input data is listed Table 4.1 and Table 4.2. Meteorological data inputs (Table 4.3) include short wave and long wave radiation, air temperature, relative humidity, wind speed and precipitation. Long wave radiation data were unavailable, but were estimated based on the fraction of cloud cover in the sky and simulated water surface temperature.

Table 4.1: DLM Physical Input Parameters

DLM Parameter	**Units**	**Calibration Period**	**Testing Period**	**Data Source**
Outlet Structure Configuration	Elevation (m)	Constant	Constant	Reclamation
Folsom Reservoir and Channel Geometry	Length (m)	Constant	Constant	ArcGIS (Reclamation MPGIS)
Reservoir Volume	m^3 at 1.5 m intervals	Constant	Constant	Reclamation
Temperature Multiplier	Growth, respiration, and Death	Constant	Constant	Calibrated
Light attenuation	Background/m	Constant	Constant	Calibrated

Table 4.2: DLM Biological Input Parameters

DLM Parameter	**Units**	**Calibration Period**	**Testing Period**	**Data Source**
Algal Growth	Maximum growth rate/d	Constant	Constant	Calibrated
Algal Respiratory	Maximum respiratory rate/d	Constant	Constant	Calibrated
Algal Mortality Maximum	mortality rate/d	Constant	Constant	Calibrated

4.2 DLM Calibration and Testing

DLM was calibrated for Folsom Reservoir on a daily time step for six months (June 1st through November 30th) in the year of 2001. DLM was found to be most sensitive to maximum layer thickness, light attenuation and algal growth parameters. However, calibrated parameters were found to be within typical ranges. The six month period corresponds to the warm and dry climate period with the greatest thermal activity. This is also the time when reservoir operators design temperature dependent release strategies. The Bureau of Reclamation collects Folsom lake vertical temperature profile records for six locations at 1.5 m depth increments approximately twice a month. Temperature profiles collected at the dam location were used to calibrate the model from June 1, 2001 to November 30, 2001 using corresponding input data. Eleven observed temperature profiles were compared to the simulated data in 2001

(Appendix E). Calibrated results produced an average overestimation of temperature by 0.37°C. Maximum and minimum over and under estimation are 4.83°C and 3.44°C respectively for any one simulated and observed comparison. The root mean square error (RMSE) for the calibration period is 1.29°C where 6% of the compared data deviates above 1°C and 2% of the compared data deviates above 2°C. The average difference between simulated and observed reservoir elevation is 0.05 m and a RMSE of 0.12 m.

The DLM model calibration was tested using observed temperature profile data June 1, 2005 through November 31, 2005. Again, eleven observed profiles were compared to simulated data (Appendix E). The testing results revealed an average overestimation of temperature by 0.18°C and a RMSE of 1.37°C. The model deviated the most during periods of suspected algal blooms in the summer and at the end of November when the reservoir de-stratified.

4.3 Multi-Objective Optimization Formulation

Each year temperature related reservoir operations are planned in preparation for the early summer through fall, or until management for downstream temperature is no longer possible. This planning process is described generally, as it could be applied at locations with similar objectives and constraints. The reservoir temperature operation plan involves input from several parties with multiple and sometimes conflicting objectives. The agency managing water supply is concerned with meeting their responsibility to deliver to water purveyors and meeting water flow or quality standards downstream. Wildlife and fisheries agencies are concerned with their responsibility to manage aquatic habitat and populations, especially those which are threatened or endangered. Power agencies are also concerned about their responsibility to provide power generation when customers need electricity. Other interests, such as recreation, are also important for most reservoir systems, but are not addressed here to simplify the number of objectives in the problem. The collective responsibilities or objectives of water supply, fishery and power agencies are linked together by one resource. The challenge is to supply sufficient information to decision makers to manage the resource, ideally in an optimal fashion. The difficultly of this problem are the conflicts between the parties responsibilities. Three potential conflicts exist:

1. Water supply (which is warm in the summer months) is released to meet water demands at the same time fish are sensitive to the water temperature

2. Releasing cool water from deep in the reservoir could provide the desired stream temperature but also could potentially circumvent power generation

3. Releasing more water than the water demand may increase hydropower generation, but it may exhaust the cold water available for later stream temperature maintenance

Several pieces of information are essential to planning for a six month (June through November) reservoir release plan including: initial storage volume, initial reservoir temperature profile, estimated water demands and requirements, meteorology, precipitation, reservoir inflow, and river temperature targets.

A set of solutions which meet the water supply, wildlife and fishery, and power agencies requirements for Folsom Reservoir is presented as a multi-objective optimization problem. The optimization is designed to search for a set of optimal reservoir release policies in a six-month (June 1st through November 30th) period. The optimal release policy is based on three objectives:

1. minimizing deviations of water delivery demand target (volume)
2. maximizing hydropower generation (energy), and
3. minimizing the deviation of the water temperature target (days of violation).

An additional advantage of the Folsom Reservoir facility is the flexibility to blend water from different elevations in the reservoir resulting in a more desirable release temperature but also a more complex release plan. The mathematical representation of the multi-objective optimization is presented as a constrained optimization problem:

$$Minimize \quad Z\left(\overline{x_{ij}}\right) = \left[z_1\left(\overline{x_{ij}}\right), z_2\left(\overline{x_{ij}}\right), z_3\left(\overline{x_{ij}}\right)\right], \forall ij \in \Omega \tag{4.1}$$

Where:

$$z_1\left(\overline{x_{ij}}\right) = \sum_{t=1}^{T}\left(-P_t\right) \tag{4.2}$$

$$z_2\left(\overline{x_{ij}}\right) = \sum_{t=1}^{T}\left|\left(D_t - \sum_{j=1}^{N} x_{ij}\right)\right| \tag{4.3}$$

$$z_3\left(\overline{x_{ij}}\right) = \sum_{t=1}^{T}\left|\left(C - W_t\right)\right| \tag{4.4}$$

Subject to:

$$P_t = \phi\left(\overline{x_{ij}}\right) \tag{4.5}$$

$$W_t = \phi\left(\overline{x_{ij}}\right) \tag{4.6}$$

$$0 \leq \overline{x_i j} \leq Q \tag{4.7}$$

The main objective function,$Z\left(\overline{x_{ij}}\right)$ in (4.1), is the minimization of decision variable vector x_{ij}. The decision variable vector x_{ij} is the quantity of water released in month i at an outlet location j, where the total number of outlets, N in equation (4.3), for all values of i and j in the feasible region Ω. Also, the time step, t, is in days where the total number of days is T.

The first objective, $z_1\left(x_{ij}\right)$ in (4.2), maximizes the hydropower generation. The relationship between the decision variable and hydropower generation, P_t in (4.5) is represented by the general variable ϕ.

The second objective, $z_2\left(x_{ij}\right)$ in (4.3), minimizes the sum of the absolute differences of the monthly delivery forecast. The delivery forecast, D_t, is an expected volume of water to meet municipal, industrial, agricultural and environmental requirements each month. This serves as a restraint on water storage to manage the cold water assets and minimizes delivery shortages.

The third objective, $z_3(x_{ij})$ in (4.4), minimizes the sum of the degree days exceeding the reservoir release temperature target. The objective is the absolute difference between the target temperature, C, and the simulated temperature represented as W_t (equation (4.6)). The generalized variable ϕ in (4.6) is found, in this application, using the DLM model. Equation (4.7) is a non-negativity constraint that prevents negative outflow and flow from exceeding a maximum value of Q.

The number of decision variables, x_{ij}, varies for the application depending on the storage elevation in the reservoir. The number of decision variables is the number of outlet elevations capable of releasing water multiplied by the desired interval to modify the reservoir release configuration. By increasing both the inlet locations and the configuration interval, the number of decision variables increases and can affect computational time.

A genetic algorithm is used to perform the multiple objective optimizations described above. An overview of the evolutionary algorithm and the non-dominated sorted genetic algorithm, NSGA-II, used to solve this problem is presented in Appendix A. The optimization consists of a series of modules which include population initialization, sort, crowding distance, selection, crossover and mutation (Deb et al., 2002).

The following describe details specific to this application of the NSGA-II algorithm. First the population size is selected by the user and initialized by random generation. The individuals or decision variables of the population are also bound by user specified constraints (Appendix C). Next, the initialized population fitness is calculated based on the objective functions. The population is then sorted by a non-dominated sorting method. The notation below follows that of Deb et al. (2002). The non-dominated sort begins with the first individuals of the population stored in a set called P^1 where the individuals are the solutions or decision variables of the objective functions. Subsequent individuals, p, are compared with individuals q of set P^1. When p dominates, or out performs the fitness of an individual in P^1 then q is removed from P^1. If the individual p is dominated by a member q in P^1, the individual has no consequence on the sort and is ignored. If the individual p is not dominated, then p is added to the set P^1. P^1 is the so called "non-dominated" solution set after all individuals in the population are checked (Deb et al., 2002). The following excerpt from Deb et al. (2002) describes the sort mathematically:

"P^1 = find non-dominated front (P)
$P^1 = \{1\}$ include first member in P^1
for each $p \in P \wedge p \notin P^1$ take one solution at a time
$P^1 = P^1 \cup \{p\}$ include p in P^1 temporarily
for each $q \in P^1 \wedge q \neq p$ compare p with other members of P^1
if $p \prec q$, then $P^1 = P^1$
$\{q\}$ if p dominates a member of P^1, delete it
else if $q \prec p$, then $P^1 = P^1$ $\{p\}$ if p is dominated by other members of P^1, do not include p in P^1"

Prior to selecting the next generation of individuals, the selection process depends on both crowding distance and sort. Following the non-dominated sort, the crowding distance of the individuals is calculated. The crowding distance is defined as the "Euclidian distance between each individual in a [Pareto] front based on their m objectives in the m dimensional hyper space" (Seshadri, 2005). The number of objectives, m, will have a corresponding number of Pareto optimal fronts and individuals for each front. The first and last individual of each sorted Pareto front is assigned an infinite crowding distance and all others are initialized to zero. For the remaining individuals, in equation (4.8) the crowding is calculated as based on Deb et al. (2002):

$$I\left(i\right)_{distance} = I\left(i\right)_{distance} + \left(I\left(i+1\right).m - I\left(i-1\right).m\right) \tag{4.8}$$

Where $I\left(i\right)$ distance is the sorted individual of objective m and $I\left(i\right).m$ is the value of the m^{th} objective function of the i^{th} individual in I.

The next generations of individuals are selected, as previously noted, based on sorted rank and crowding distance. The NSGA-II selection uses a binary tournament selection with a crowded-comparison-operator to choose a well spread population of individuals. The partial order crowded-comparison-operator in equation (4.9) is defined from Deb et al. (2002) as:

$$i \prec_n jif\left(i_{rank} < j_{rank}\right) or \left(i_{rank} = j_{rank}\right) and \left(i_{distance} > j_{distance}\right) \tag{4.9}$$

Where i_{rank} and j_{rank} are an individual's rank from the non-dominated sort and $i_{distance}$ and $j_{distance}$ are the crowding distance from either the same or differing m Pareto fronts. The next step in the process calls for genetic operations to mix and morph the individual solutions for the offspring population. This is accomplished by two methods: (1) simulated binary crossover and (2) polynomial mutation. Both are described in an excerpt from Seshadri (2005):

"Simulated Binary Crossover:

$$c_{1,k} = \frac{1}{2}\left[\left(1-\beta_k\right)p_{l,k} + \left(1+\beta_k\right)p_{2,k}\right] \tag{4.10}$$

$$c_{2,k} = \frac{1}{2}\left[\left(1+\beta_k\right)p_{l,k} + \left(1-\beta_k\right)p_{2,k}\right] \tag{4.11}$$

Where $c_{i,k}$ is the i^{th} child with k^{th} component, $p_{i,k}$ is the selected parent and $\beta_k\left(\geq\right)$ is a sample from a random number generated having the density:

$$p\left(\beta\right) = \frac{1}{2}\left(\eta_c+1\right)\beta^{\eta_c}, if 0 \leq \beta \leq 1 \tag{4.12}$$

$$p\left(\beta\right) = \frac{1}{2}\left(\eta_c+1\right)\beta^{\eta_c}, if 0 \leq \beta \leq 1 \tag{4.13}$$

This distribution can be obtained from a uniformly sampled random number u between (0,1). η_c is the distribution index for crossover (this determines how well spread the children will be from their parents). That is:

$$\beta(u) = (2u)^{\frac{1}{(\eta+1)}} \tag{4.14}$$

$$\beta(u) = \frac{1}{[2(1-u)]^{\frac{1}{(\eta+1)}}} \tag{4.15}$$

Polynomial Mutation

$$c_k = p_k + \left(p_k^u - p_k^l\right)\delta_k \tag{4.16}$$

Where c_k is the child and p_k is the parent with p_k^u being the upper bound (the decision space upper bound and lower bound for that particular component) on the parent component, p_k^l is the lower bound and δ_k is [a] small variation which is calculated from a polynomial distribution by using:

$$\delta_k = (2r_k)^{\frac{1}{\eta_m+1}} - 1, if r_k < 0.5 \tag{4.17}$$

$$\delta_k = 1 - [2(1-r_k)]^{\frac{1}{\eta_m+1}} - 1, if r_k < 0.5 \tag{4.18}$$

r_k is an uniformly sampled random number between (0,1) and η_m is [the] mutation distribution index."

Finally, the next generation of individuals is created by joining the offspring with the current generation based on their performance. The next generation is known as the elitist population and is again sorted for non-dominance. All selected offspring are joined to the current population. If the combined set exceeds the number of members in the population then individuals are removed based on crowding distance until the population has been reached. This new set of offspring becomes the next parent generation which repeats the entire process of sorting, calculation of crowding distance, selection, crossover, and mutation until the maximum number of user defined generations is met (Deb et al., 2002).

Table 4.3: DLM Hydroloby and Meteorology Input Parameters

DLM Parameter	**Units**	**Calibration Period**	**Testing Period**	**Data Source**
River Inflows	m^3/s	June 1, 2001 – November 30, 2001	June 1, 2005 – November 30, 2005	CDEC (FOL)
Reservoir Outflows	m^3/s	Same as above	Same as above	CDEC (FOL) and Reclamation
River Inflow Temperature	°C (average daily)	Same as above	Same as above	Reclamation
Folsom Temperature Profiles at Dam	°C (on average 1.5 m intervals)	11 profiles (approx.2 per month) June 1, 2001 – November 30, 2001	11 profiles (approx. 2 per month) June 1, 2005 – November 30, 2005	Reclamation
Short Wave Radiation	Watts/m^2 (daily)	June 1, 2001 – November 30, 2001	June 1, 2005 – November 30, 2005	CIMIS (Davis 2001 and Fair Oaks 2005)*
Cloud Cover	Percent cover (daily)	Same as above	Same as above	NWS
Air Temperature	°C (average daily)	Same as above	Same as above	CIMIS (Fair Oaks)
Relative Humidity	Percent (average daily)	Same as above	Same as above	CIMIS (Fair Oaks)
Wind Speed	m/s	Same as above	Same as above	CDEC (FLD)
Precipitation	mm (daily)	Same as above	Same as above	CIMIS (Fair Oaks)

* *Note:* June 1, 2001 – November 30, 2001 data was considered suspect due to inconsistencies in comparison with other local data and data was replaced with the CIMIS Davis station data.

5. MODEL APPLICATION

The optimization problem as formulated suggests optimal multi-objective reservoir release policy solutions for a six month period from June 1st through November 30th to meet water delivery, in-stream temperature, and hydropower objectives. The desired outcomes are a set of solutions that describe optimal reservoir release policies for the set of the described objective functions. Tradeoffs of the objectives also are desired to evaluate the potential costs to each agencys objective. Although the presented mathematical formulation could be solved by various optimization methods, it is solved here using an evolutionary algorithm because of its advantage for non-linear objective functions (Deb, 2001).

The presented problem is solved by using linked simulation-optimization models. Reservoir dynamics and outflow temperature are found using the DLM model and are iteratively used within the genetic optimization algorithm. Figure 5.1 illustrates the flow of data from the optimization routine to the reservoir simulation model. The population of "solutions" generated by the genetic algorithm is the volume and locations of flow released from the reservoir and passed to the DLM model where outflow temperatures are calculated. In the optimization program, the user has control of the population size and the number of generations or iterations.

5.1 Model Assumptions and Inputs

The solutions to the multi-objective reservoir problem are best appreciated by understanding the assumptions, input data, and initial conditions. A series of assumptions and data inputs were made to simplify the Folsom Reservoir system. These application assumptions are made in addition to assumptions for both the temperature simulation and optimization models. A summary of application assumptions, input data and initial conditions are listed in Appendix C.

Rather than generating synthetic data to represent environmental conditions, historical data was used. Selecting the initial conditions and historical period determine the level of difficulty for the problem. Two time periods were chosen to test the optimization, one that challenged the algorithm's decision making ability and another less complex period for comparison. Two six month periods, June – November in year 2001 and 2005, were selected. The winter and spring of 2000 – 2001 was drier than normal resulting in lower reservoir storages in the beginning of June. In contrast, 2005 was wetter than normal which resulted in higher reservoir storage in June.

For both time periods, the total number of days, T in equation (4.2) is 183, beginning June 1 and ending November 30. Although thermal lake stratification is typical for both time periods as seen in Figure 5.2, low initial storage and warmer

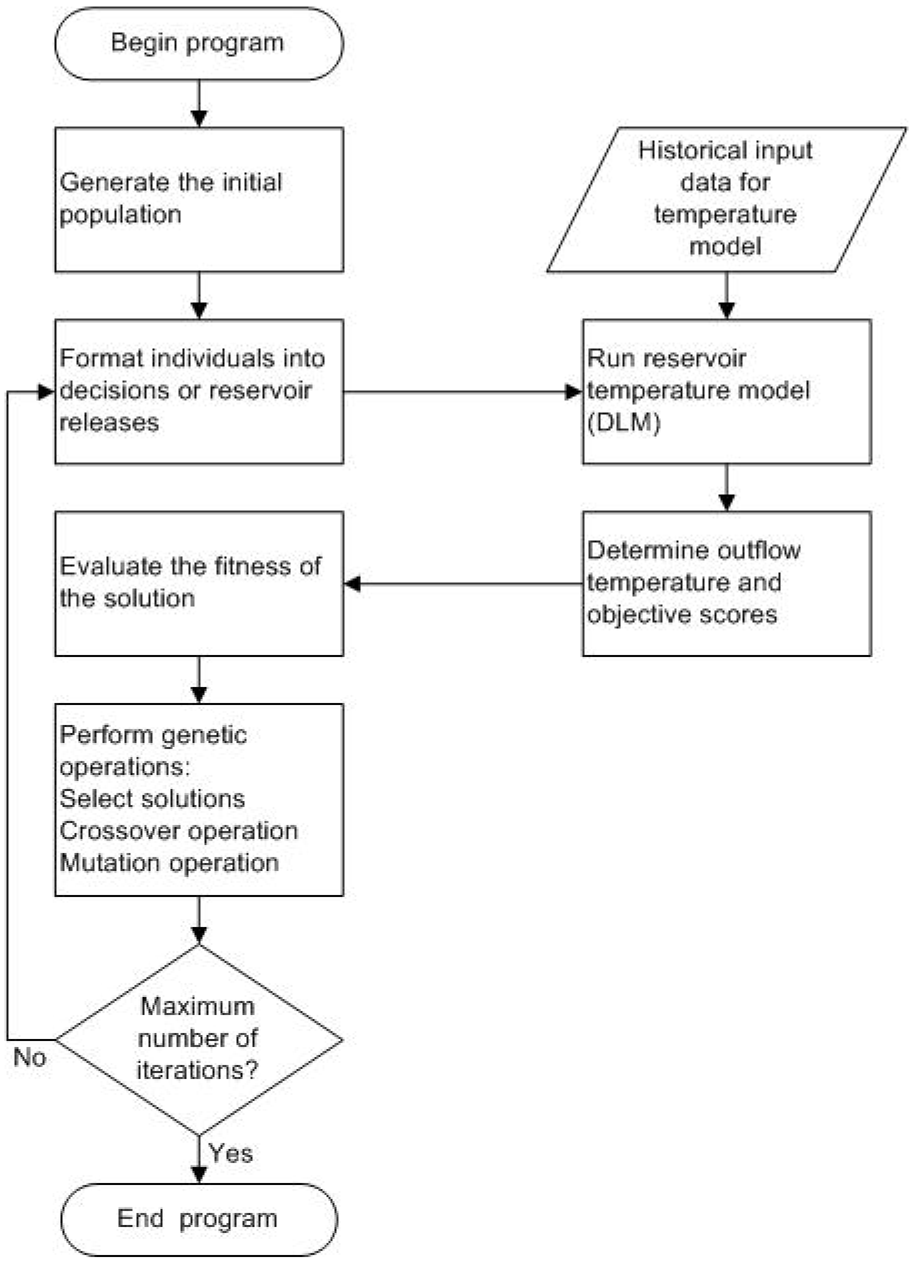

Figure 5.1: Multi-Objective Optimization Program Flowchart

reservoir water temperatures exacerbated meeting year 2001 downstream temperature control standard.

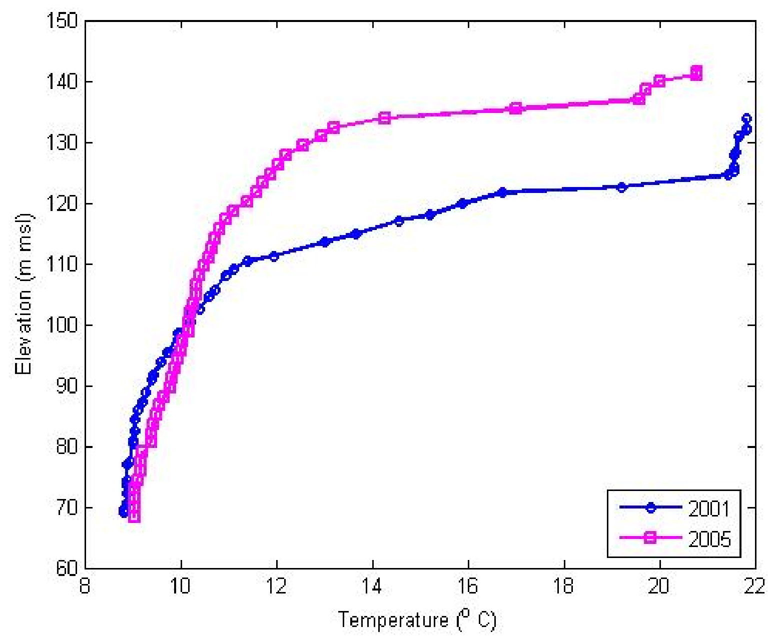

Figure 5.2: June 1st Observed Folsom Reservoir Vertical Temperature Profiles in Year 2001 and 2005

The meteorological conditions for both 2001 and 2005 appear to have similar magnitude and frequency of events. Sunny and warm (Figure 5.3 and Figure 5.4) days with moderate wind and little precipitation (Figure 5.5 and Figure 5.6) are typical in the summer. Also typical for both years is cooler air temperature starting in the early fall with some precipitation, Figure 5.6, (and increased relative humidity as seen in Figure 5.4) beginning in the late fall.

Although meteorological conditions are surprisingly similar between the two years June though November, the water-year hydrology and water temperature is markedly different. In general, tributary inflows for both years are lower in the summer months and increase quickly in response to precipitation events in the fall. Year 2001 inflows from the North Fork and South Fork of the American River are shown in Figure 5.7. This year combined flows peaked at 55 m^3/sec in June. The 2001 combined average flows for this period were 22 m^3/sec and averaged 17°C. In contrast, June of 2005 was preceded with a larger quantity of snow pack than the spring of 2001 which resulted in relatively high snow-melt runoff (Figure 5.8). Year 2005 yielded combined peak inflows of 319 m^3/sec in June and an average of 75 m^3/sec with cooler water temperatures averaging 15°C for the entire period.

Meteorology inputs, hydrology inputs, and water demand from the reservoir are uncertain six months previous. However, in this application it is assumed that similar historic years would yield similar conditions. The two application simulations

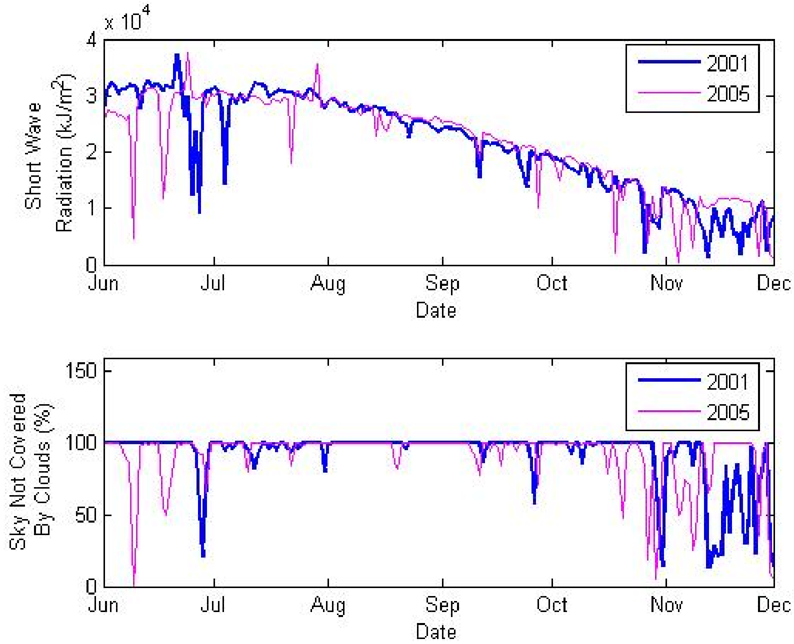

Figure 5.3: Meteorological Input Data June – November 2001 and 2005: Short Wave Radiation and Percent of Sky Not Covered By Clouds

use historical meteorological and hydrologic data from water year 2001 and 2005. An investigation of input uncertainty on optimization results is left for future study.

Another input to the model is the assumed quantity of water to deliver. This is determined by a projection of demand on the system by the agency operating the reservoir. Reclamation routinely forecasts demands each month for a twelve-month outlook. These forecasted demands are assumed to sufficiently estimate the actual deliveries, or outflow released from Folsom Reservoir. A monthly delivery forecast (D_t in equation (4.3)) from June to November is generated in June using a 90% exceedance hydrology forecast. Figure 5.9 shows the 90% delivery forecast and compares it to actual deliveries made in June 2001 for the months June through November 2001. A similar comparison is made for year 2005 in Figure 5.10. The year 2001 release forecast has a maximum release difference of 11% (a volume of 8 10^3 m^3) in November and year 2005 has a maximum difference in June of 17% (a volume of 72 10^3 m^3) in June.

Several assumptions were made to simplify the release of water from the reservoir to meet demands downstream. In reality, municipal water is served from Folsom Reservoir from selective withdrawal in the lake upstream from the dam outlet works. Here it is assumed the release is made at the outlet works and delivered. The outlet temperature apparatus at Folsom Reservoir requires operators to manually adjust the temperature shutters on the penstock. The adjustments to the outlet configuration in the model are assumed limited to once per month. This approximates the frequency of historical temperature shutter operations (Washburn, 2005). The number

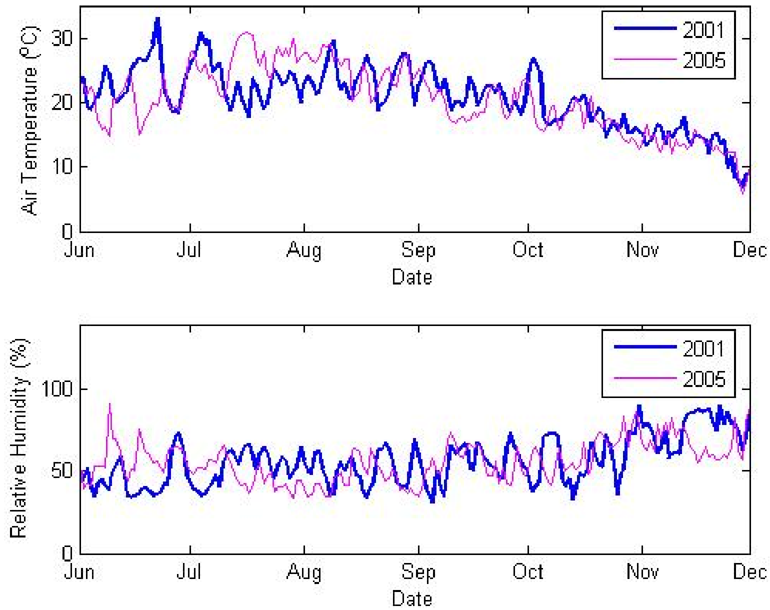

Figure 5.4: Meteorological Input Data June – November 2001 and 2005: Air Temperature and Relative Humidity

of reservoir outlet elevations, N in equation (4.3), is seven: spillway gates, all penstock shutters closed, upper penstock, middle penstock, lower penstock, upper tier river outlet, and lower tier river outlet (for application, if the initial storage of the reservoir is lower than the upper most outlet elevations, then the total number of outlet elevations for use is less). In addition, a minimum of 8.2 m of head above the penstock opening is an operational restriction for power generation and is relaxed to zero for this application.

Downstream temperature at the Watt Avenue Bridge control location is not explicitly modeled. Instead, the release temperature target C in equation (4.4) is 15.5°C, which is used as a surrogate temperature in lieu of calculating the temperature flux downstream from the reservoir to the control point. This is a conservative assumption compared to historical release quantity and temperature relationship data used by Reclamation (Yaworsky, 2005).

Several assumptions also are made for hydropower generation. Equations (5.1) through (5.4) describe the hydropower calculation at Folsom Reservoir:

$$R = 10^{A - B\log(Cx_{ij}) + D\log(Cx_{ij})^2} \tag{5.1}$$

$$G = HE - R \tag{5.2}$$

$$e = FG - K \tag{5.3}$$

$$P_t = ex_{ij}L \tag{5.4}$$

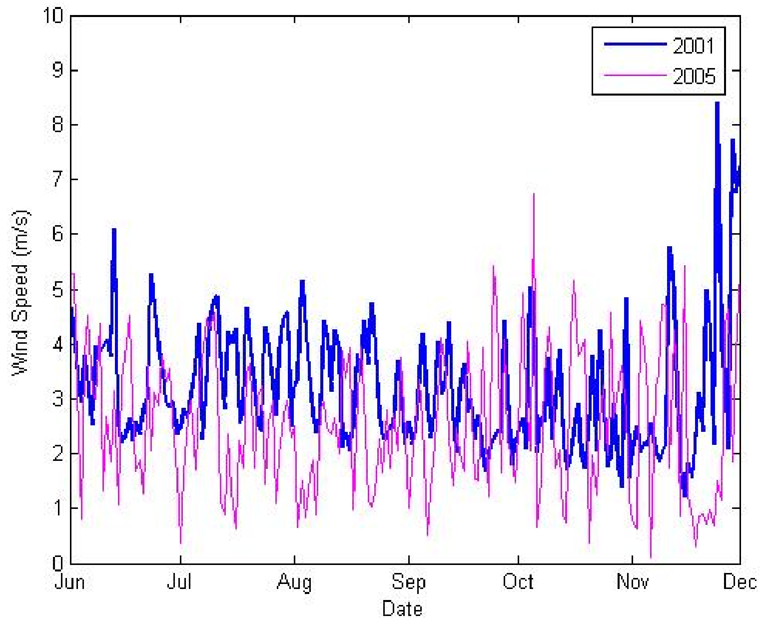

Figure 5.5: Meteorological Input Data June – November 2001 and 2005: Wind Speed

The variable R in equation (5.1) represents the "tail race" elevation increase (feet) as a function of flow out of the penstocks. The reservoir elevation, H (meters) is converted to feet with constant E, less the tail race, R, and yields G, the gross head (feet) in equation (5.2). Equation (5.3) is the calibrated efficiency, e, of the hydropower unit given G, the gross head. Equation (5.4) is the hydropower generated per month, P_t (kilowatt hours) as a function of outflow, x_{ij} , and efficiency, e. Equations (5.1) – (5.4) constants are listed in Table 5.1.

Table 5.1: Hydropower Equation Constants

Constant Variable	**Value**
A	2.11
B	0.04
C	2446.60
D	0.05
E	3.28
F	0.93
K	16.28
L	1.98

Maximum outflow from any outlet elevation Q equation (5.7), is 18,000 10^3 m^3/month. This is physically unrealistic for the lower tier river outlet but is left unconstrained for the genetic algorithm to explore this alternative. However, artificial

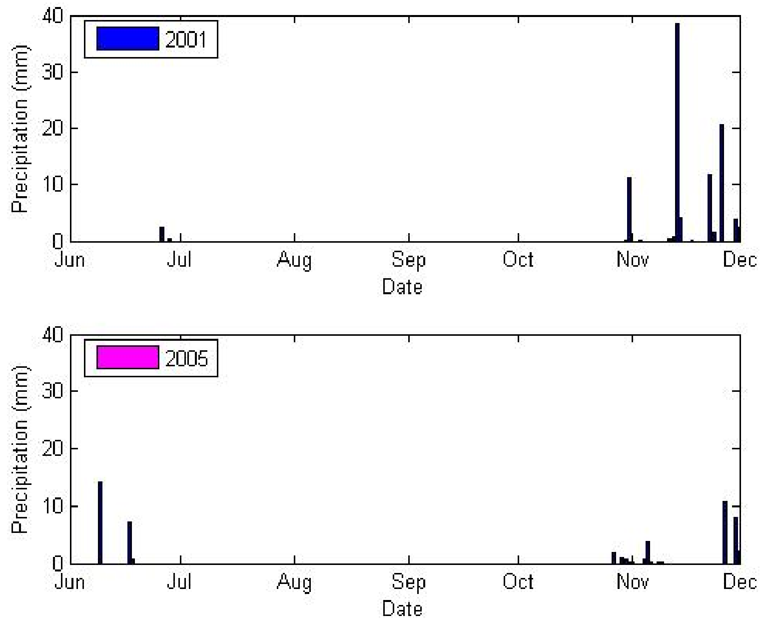

Figure 5.6: Meteorological Input Data June – November 2001 and 2005: Precipitation

constraints are imposed to avoid an infeasible reservoir temperature simulation by using undesirable fitness values. For example, if total releases for the six month period exceed 2,500 10^3 m^3, then a poor fitness value is assigned to the solution set and the reservoir temperature model is not run.

For all year 2001 optimizations, four outlets were used (upper, middle, lower penstock shutters, and the lower tier river outlet) because the reservoir's initial storage conditions were lower than the upper most outlets. Year 2005 optimizations use five outlet locations, (all penstock shutters closed, upper, middle and lower penstock shutters, and the lower tier river outlet). For the six month planning horizon in year 2001 there are 24 decision variables determining the volume of outflow and location of release from the reservoir. In year 2005 there are 30 decision variables.

Due to the many decision variables and the desire to reduce optimization run time, a set of population initialization seeds were developed for both years 2001 and 2005. The seed population consists of decision policy sets tailored specifically for this application. The following seeds are used in this application:

1. The historical water supply delivery, hydropower and temperature control configuration.

2. The remaining population is determined by randomly selected release volumes for n-1 outlets each month. Outlet n, also randomly selected, equals the difference between the sum of all n-1 outlets minus the six-month target delivery.

The historical release configuration is used to determine whether it is a non-dominated

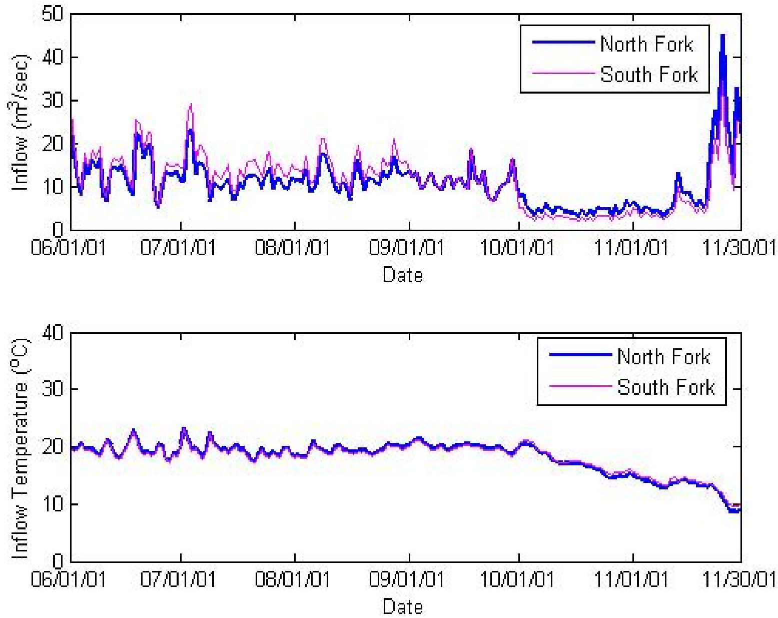

Figure 5.7: North Fork and South Fork American River Inflow and Temperature into Folsom Reservoir, June – November 2001

solution and the custom random seed procedure (also presented in Appendix E) attempts to minimize the delivery target deviation.

Parameter values in the genetic algorithm optimization routine resulted from trial and error experience. Populations of 100 and 200 individuals and the number of generations between 100 and 1500 were tested. Results use a population of 100 and 1500 generations, smaller numbers of individuals and generations yielded solutions sets with spreads which were either too sparse or too wide, respectively. Table 5.2, Table 5.3, and Table 5.4 compares the model performance with historical operation performance. The differences in the year 2001 simulation are in part due to the bypass of hydropower in November. The simulated monthly decision time step did not accurately capture the historical lower tier river outlet operation which began mid-November. This result underestimates actual hydropower generation and aids in reducing the number of days in which the temperature target was exceeded. Downstream heating in-stream is also suspected to increase the number of days exceeding the temperature target, despite the conservative target release from the reservoir. Additional simulation performance information is presented in the sensitivity analysis, Section 6.1.

Several factors within the NSGA-II optimization algorithm influence the progress and final result of the solution set. These assumptions regard sorting, crowding distance designation, selection, crossover, and mutation. The NSGA-II uses the non-dominated sort method described in Section 4.3. No controls exist for the user to adjust the non-dominated sort. Following the sort, the crowding distance method is

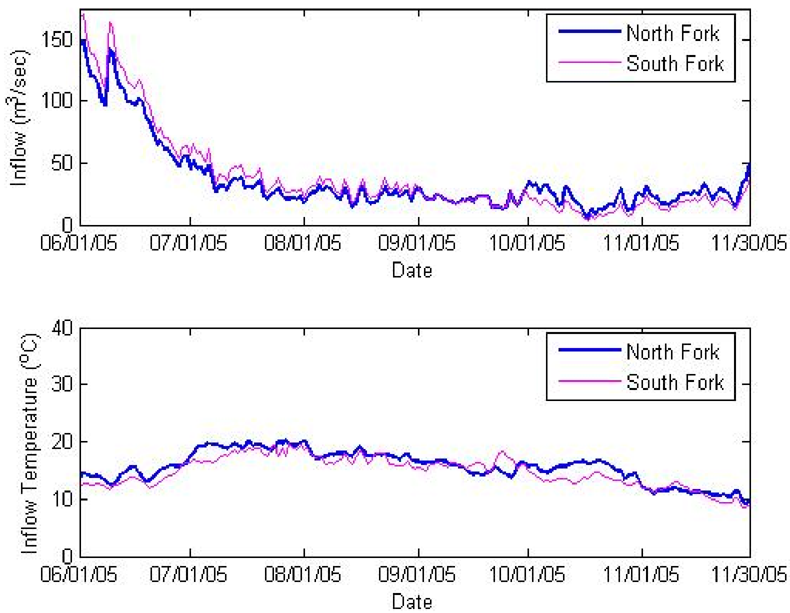

Figure 5.8: North Fork and South Fork American River Inflow and Temperature into Folsom Reservoir, June – November 2005

Table 5.2: Comparison of Historical and Simulated Hydropower Performance

Water	**Total Hydropower (GWh)**	
Year	**Historical**	**Simulated**
2001	152	110
2005	354	354

based on the assumption of an infinite crowding distance assigned to the boundary individuals. This affects the spread of the solution as suggested by Seshadri (2006). The parent individuals to produce offspring are selected using a binary tournament selection. This is based on the size of the mating pool which is assumed equal to half the initial population pool. Also assumed is the size of the tournament for the selection process, here it is two competing groups. From the selected parents, offspring are created based on the crossover of the parents traits. Crossover in this version of the NSGA-II algorithm is based on only the real-coded genetic algorithm rather than binary-coded. The crossover uses both the simulated binary crossover and polynomial crossover techniques. The parameters η_c (crossover distribution index) and η_m (mutation distribution index), as described in section 4.3, have a value of 20 for both. The sensitivity of the solution to these parameters is discussed in section 6.1.

The optimization and simulation model was run using an Intel Pentium D 930, 3.0 GHz dual processor with 2 Gb of RAM on a desktop personal computer system.

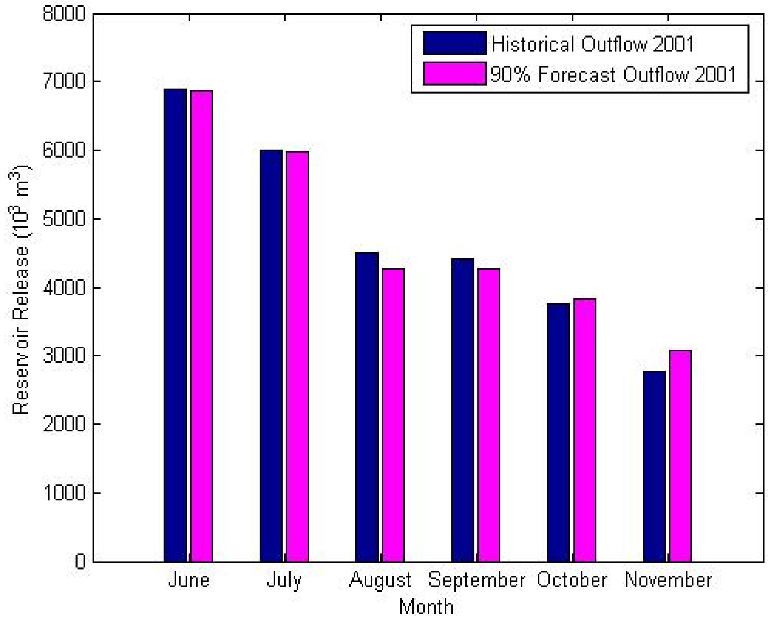

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Figure 5.9: Comparison Between the 2001 Historical and 90% Exceedance Forecast (Created in June) for Folsom Reservoir Outflow Volume June – November

Table 5.3: Comparison of Historical and Simulated Delivery Deviation Performance

Water Year	**Delivery Deviation (10^3 m^3) Historical**	**Simulated**
2001	0	0
2005	0	0

The software used to run the optimization and simulation package was MatLab©. The NSGA-II, C code (Deb et al., 2002) was ported to MatLab©and tested by Seshadri (2006). The NSGA-II MatLab©code, calls *evaluate_objective.m*, and was modified for the Folsom Reservoir problem (Appendix G). The DLM model FORTRAN 77 executable was called dynamically from NSGA-II to simulate reservoir outflow temperatures. The results were prepared and post-processed using MatLab©and R. Average model execution time of the DLM simulation run with a spatial discretization of 5 m is 2.15 seconds. An optimization execution time with a population of 100 individuals and 750 generations is 44.8 hours (1.8 days). Optimizations with a population of 100 individuals and 1500 generations require 93.8 hours (3.9 days) of runtime. A parallel processing system could significantly improve run time.

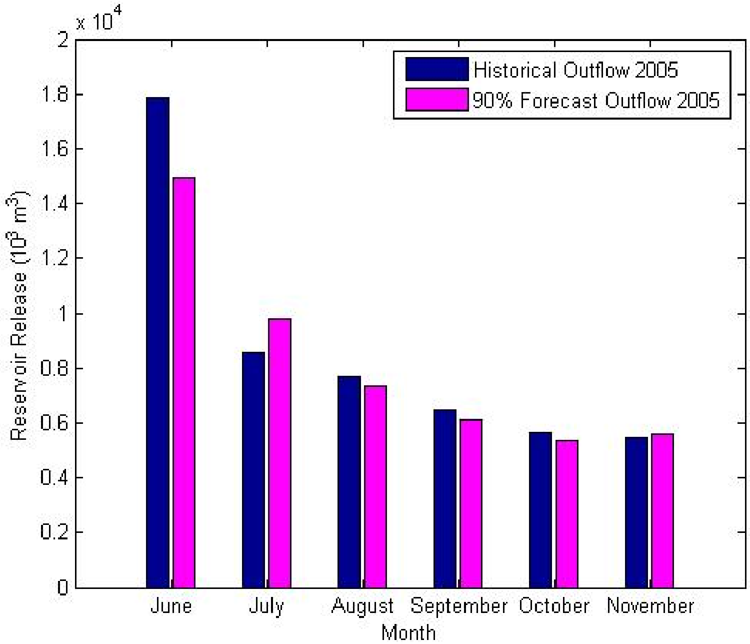

Figure 5.10: Comparison Between the 2005 Historical and 90% Exceedance Forecast (Created in June) for Folsom Reservoir Outflow Volume June – November

Table 5.4: Comparison of Historical and Simulated Temperature Exceedance Performance

Water	**Temperature Exceedance (days)**	
Year	**Historical**	**Simulated**
2001	122	85
2005	2	2

5.2 Model Results and Discussion

Optimal reservoir releases were found to maximize hydropower, minimize delivery target deviations and minimize temperature target exceedance for two years, 2001 and 2005. Year 2001 has more challenging operating conditions with less initial storage volume and warmer reservoir temperatures. In contrast, year 2005 is less difficult to operate, with more favorable storage and temperature conditions. Both results consist of non-dominated optimal sets of 100 population solutions run for 1500 generations. Evaluations of the results examine both the performance, the fitness of the objectives, and the corresponding decision variables or reservoir release policies for each year.

5.2.1 *Scenario 1: Year 2001 Results*

The performance of year 2001 non-dominated solution set is presented in Table 5.5. Although, the statistics presented do not represent the performance of a single release policy set, it summarizes an individual objective performance within its range. The performance ranges (Table 5.5) also reveal some generalizations of the non-dominated solution set. This problem constrains the total quantity of release of the target delivery to plus or minus a volume of 100 10^3 m^3 but does not constrain the month of delivery. Delivery deviation under- and over-release water from Folsom Reservoir, indicating a benefit to either total hydropower generation or the temperature target objectives. All non-dominated solutions exceeded the temperature target for at least 13 days and up to a maximum of 128 days (out of 183 days). In addition, the spread of the solutions may also indicate of the range of total hydropower; a range of optimal solutions from 111 to 164 GWh.

Table 5.5: Year 2001 Non-Dominated Solution Performance Ranges

Objective	**Total Hydropower Generation (GWh)**	**Delivery Target Deviation (10^3 m^3)**	**Temperature Target Exceeded (days)**
Minimum	111	102	13
Maximum	164	97	128
Mean	145	21	55
Median	148	30	52

More specific examination of the objective performance describes the possible performance tradeoffs. Tradeoffs are presented to quantify the relationships between all objectives in the non-dominated set. Figures 5.11 – 5.13 depict the comparisons amongst the objectives. Trends in temperature target and delivery deviation (Figure 5.11) indicate there is no tradeoff trend, despite an advantage to foregoing releases below the delivery target or releasing more water above the delivery target for either hydropower or temperature. If there were no advantage for other objectives, the delivery target deviation would be zero for all individuals of the population. There is also tradeoff relationship between total hydropower released and temperature target exceeded shown in Figure 5.12. The tradeoff for the entire performance range is well described with an exponential curve:

$$y = 0.37e^{0.0334x} \tag{5.5}$$

Where x GWh of energy result in y days of temperature exceedance (R^2 of 0.77). One such example is the least number of days the temperature target is exceeded, 13 days, with near zero delivery target deviation, but at a cost to hydropower, only 119 GWh generated.

The lack relationship between total hydropower generation and delivery target deviation, as it appears in Figure 5.13, reveal no tradeoff. Hydropower generation in many of the release decision solution sets is a function of delivery. The only exception occurs when a release bypasses the turbines through the lower tier river outlet. The release policies are explored further in the decision variable evaluation below.

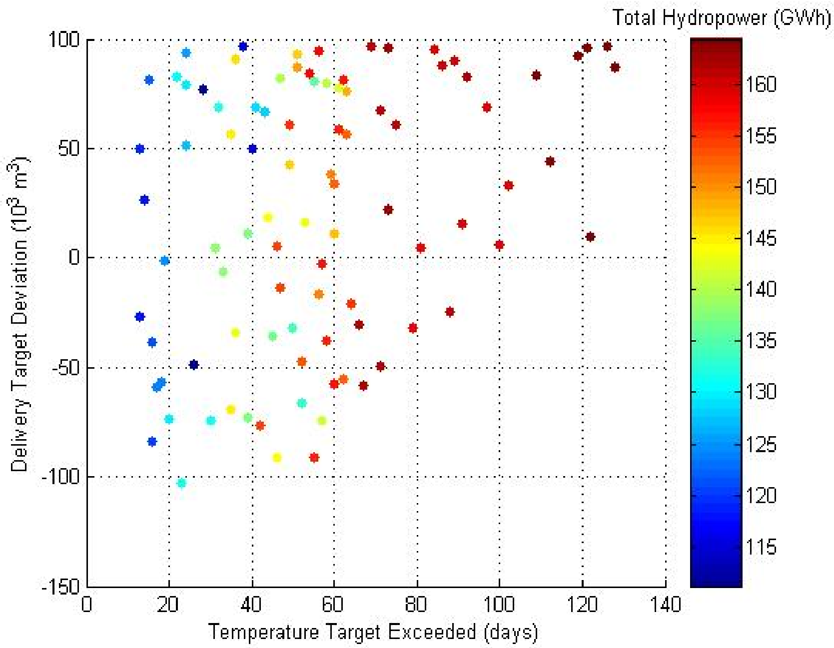

Figure 5.11: Year 2001 June – November Temperature Target Exceedance and Delivery Target Deviation Tradeoffs

Release decisions for Folsom Reservoir specify the quantity of release from each outlet elevation and for each month, June through November. An optimization such as this provides insight as to what kind of tradeoff to one or more of the objectives may be desirable in advance. Year 2001 is an example where releases were made from the lower tier river outlet which bypassed hydropower generation. The simulation and optimization results provide a suite of release decisions for a variety of objective performance combinations also including hydropower bypass.

Figure 5.14 depicts all of the release decision combinations from the non-dominated solution set for year 2001. First note there are only four release outlet elevations, (1) upper penstock, (2) middle penstock, (3) lower penstock, and (4) lower tier river outlet. The information is displayed in terms of total hydropower generation and was arbitrarily selected; results for delivery target deviation and temperature target deviation are similar. The release decisions frequently use the upper penstock in June and July. The middle penstock peaks for nearly all of the range of hydropower solutions in August. The lower penstock is used in September generally for lower hydropower generation solutions. The lower tier river outlet releases for the last months of the simulation, October and November, reducing hydropower generation.

A range of non-dominated release decisions specific to year 2001 events and conditions are shown in Figure 5.15. This illustrates release volumes and locations

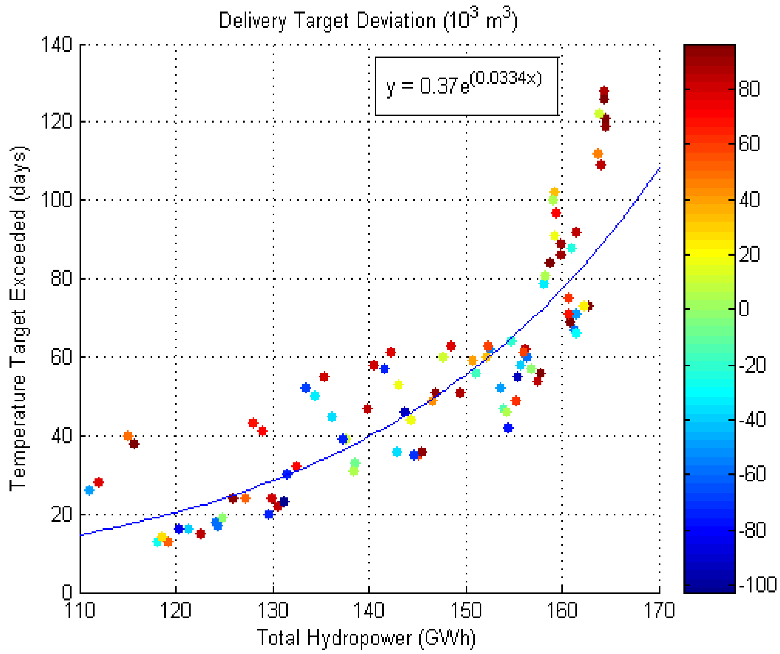

Figure 5.12: Year 2001 June – November Total Hydropower and Temperature Target Exceedance Tradeoffs

for the six month period that represent a high, mid and low range of the objective performances. All except one set (high delivery deviation) show a blending of releases in each month. Some of the low hydropower solutions also blend a small quantity of water from the lower penstock or river outlet. The 2001 historical release configuration was not found as a non-dominated solution, but a very similar variation was (see low performance for the temperature exceedance). The high performance range, on the other extreme, releases water for total hydropower generation from the upper and middle shutter outlets. In the mid range, or the compromised solution, the non-dominated result for the delivery deviation and hydropower generation is a nearly exclusive release of water in August from the middle outlet. Figure 5.16 illustrates a statistical analysis of the 100 individuals in the population by outlet location and month. The graphic shows the first and third quartiles (variants of each), the median and the upper and lower whiskers, and approximates the 95% confidence interval highlighted in yellow (Hornik, 2006). The solutions appear to blend from multiple outlets especially in September and November. Releases in September, historically from the lower and middle outlet, are found with greater range of frequency in the upper and lower outlets. This is also true in November where the non-dominated solutions release from all outlets rather than exclusively from the lower and river outlets.

In summary, year 2001 non-dominated decision variable results show some advantage to over-release and under-release for either hydropower or temperature benefit. In addition, the tradeoff between hydropower generation and temperature

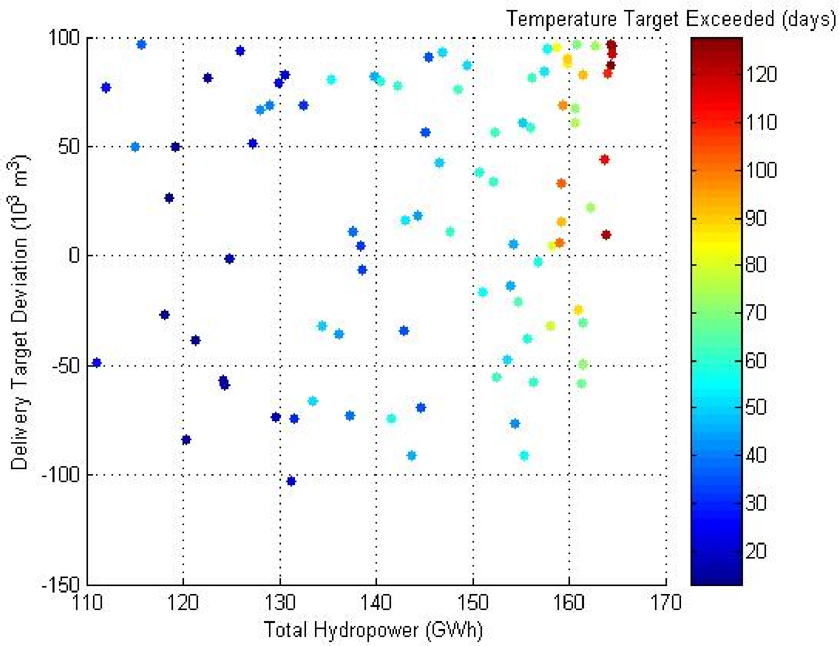

Figure 5.13: Year 2001 June – November Total Hydropower and Delivery Target Deviation Tradeoffs

appears non-linear. As additional total hydropower is generated, the days of temperature exceedance exponentially increases. The non-dominated release configurations indicate that blending from multiple locations is beneficial for year 2001 conditions. There also appear to be no generalized tradeoffs between delivery deviation and hydropower delivery (due to hydropower bypass) and delivery deviation and temperature exceedance.

5.2.2 Scenario 2: Year 2005 Results

For comparison, year 2005 results are presented to demonstrate the effect of different initial conditions on Folsom Reservoir operations. Median performance for year 2005 objectives are 355 GWh of total hydropower generation, a delivery target deviation of 95 10^3 m^3, and 43 days that exceed the temperature target (Table 5.6). Again, these are statistical values that do not represent any one particular set of release decisions. Other range of performance statistics are also listed in Table 5.6. The delivery deviation range does not span zero in this scenario and indicates either benefits to hydropower generation or the temperature target only while delivering more water than the delivery target. In year 2005 the initial reservoir volume was greater (1.18 billion m^3 in year 2005 compared with 858 million m^3 in year 2001) and projected releases were higher (55,517 10^3 m^3 in year 2005 compared with 28,271 10^3 m^3 in year 2001) hence the potential for greater hydropower generation than year 2001.

Year 2005 tradeoffs are shown in Figure 5.17, Figure 5.18, and Figure 5.19.

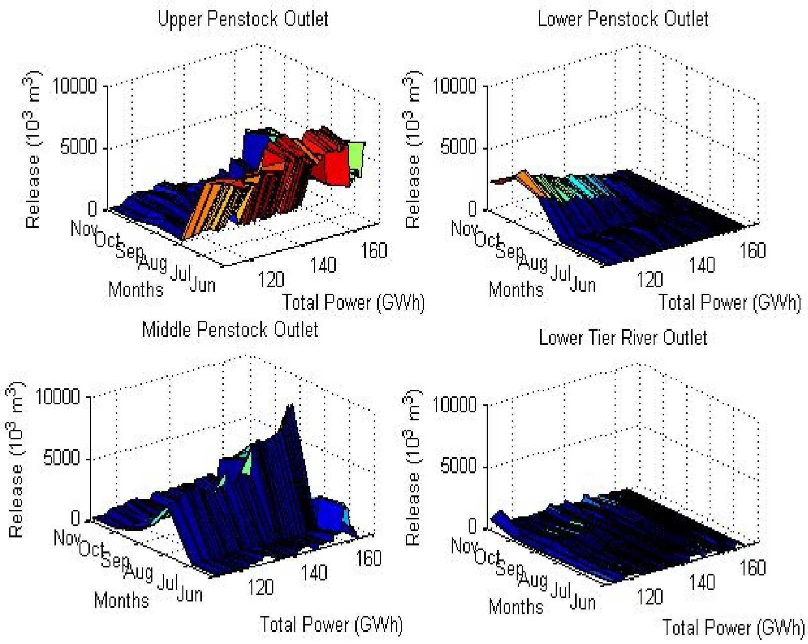

Figure 5.14: Year 2001 Non-Dominated Total Hydropower Solutions by Reservoir Outlet Release Location

Figure 5.17 illustrates the performance relationship between temperature target exceedance and delivery target deviation. This scenario's non-dominated solution set has no advantage to release less water than the delivery target. However, there is no general trend in the tradeoff associated with temperature exceedance and water delivery deviation. The objective results for delivery target deviation, with a few exceptions, are either near 100 10^3 m^3 or 0 m^3.

The relationship between total hydropower generation and temperature target exceedance is shown in Figure 5.18. With a few exceptions, the tradeoff between hydropower and temperature target days is undefined. A maximum of approximately 356 GWh of hydropower can be generated for the entire range of temperature exceeded days. The historical configuration of releases is a non-dominated solution and the objective performance is located where the temperature exceeded is 2 days and the total hydropower generated is 354 GWh. Each of the 11 solutions with less than approximately 356 GWh of hydropower generation and coincidently are near zero delivery target deviation, release from the lower tier river outlet.

There also is a trend between delivery target deviation and total hydropower generation (Figure 5.19). The relationship between the two occurs at two locations, one along the zero delivery deviation and the other again along the maximum total hydropower generation of approximately 356 GWh. Despite the trend, there is no generalized tradeoff between the two objectives. However, the solution set is sparsely populated with objective performances between the zero and 50 10^3 m^3 delivery target deviations. This bias favors the hydropower objective and may indicate a solution

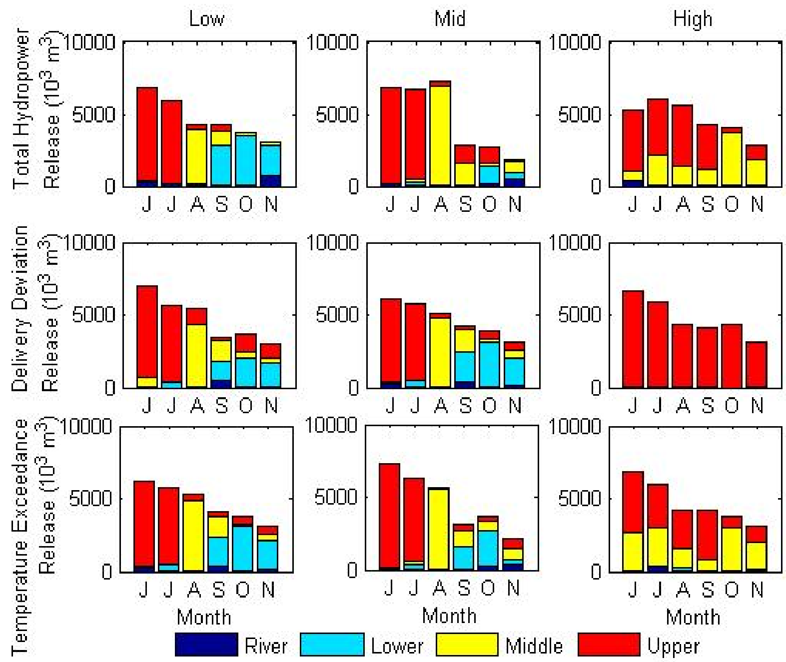

Figure 5.15: Year 2001 Release Policies (From Low to High Performance Fitness Left to Right)

requiring a greater number of generations or a greater population.

Figure 5.20 represents all of the non-dominated release decisions for year 2005 with respect to temperature target exceeded. In year 2005 the reservoir volume was greater than in year 2001 and an additional outlet elevation (all shutter penstock outlet) was available. These non-dominated solutions indicate that use of each outlet elevation was beneficial for one or more objectives. The lower tier river outlet is exercised more frequently when the temperature target exceedance is above 50 days. However, for comparison, the historical release operation from Folsom Reservoir in year 2005 did not use the lower tier river outlet to bypass hydroelectric power generation.

The range of release decisions are again examined by illustrating the minimum, mid-range and maximum objective performances (Figure 5.21). Each configuration uses a blended release rather than a single release location and sometimes from more than two locations. By comparing the mid and high range temperature target exceeded objective, the release configurations are similar except for October. For the high range configuration, the October releases from all shutter locations yielded a higher temperature exceedance, despite the use of the lower tier river outlet earlier in the season. Further analyses of the release decisions quantify the discussed relationships.

A complementary statistical analysis of the year 2005 release configurations is also presented in Figure 5.22. Observations describe both the quantity and timing of releases from the non-dominated solution set, as described previously, with the first

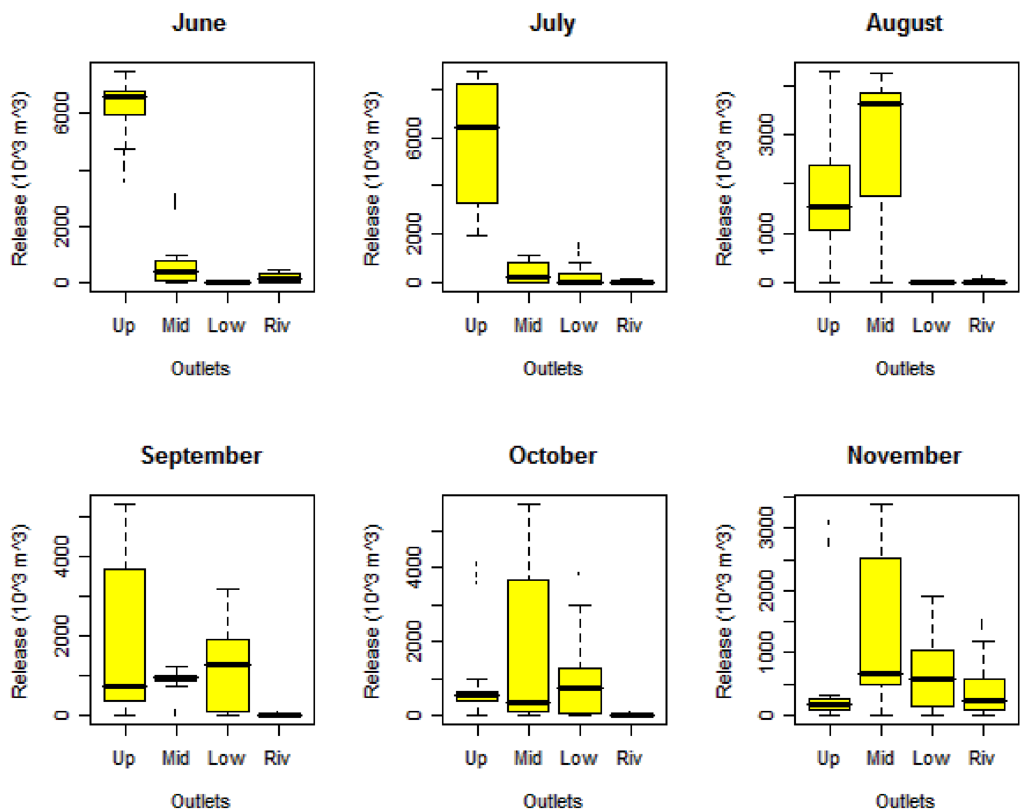

Figure 5.16: Year 2001 Evaluation of Monthly Release by Outlet

and third quartile (variants), median and 95% confidence interval. June has the least variation in the quantity of release and interestingly from all shutters, upper, middle and lower outlets. September also has surprising results; blending from a wide variety of all shutter and middle outlets. October and November are also using three and four outlets, respectively, to blend temperatures. In addition, the lower river outlet is almost never used with the exception of some outliers and intuitively should be the case considering the historical releases were capable of a low number of temperature target exceedance without bypassing hydropower using the lower tier river outlet.

In summary, year 2005 non-dominated decision variable results appear to bias the hydropower objective. More solutions tend to maximize the delivery deviation constraint of 100 10^3 m^3 rather than exploring the solutions near the zero delivery deviation. The year 2005 solutions, however, indicate no advantage from releasing less water than the delivery target, unlike the year 2001 solutions. Also, the non-dominated release configurations more frequently blend from two or more locations rather than one. No generalized tradeoff curve is associated with the year 2005 solution set amongst any of the objectives.

Table 5.6: Year 2005 Non-Dominated Solution Performance Ranges

Objective	**Total Hydropower Generation (GWh)**	**Delivery Target Deviation (10^3 m^3)**	**Temperature Target Exceeded (days)**
Minimum	256	0	2
Maximum	356	99	74
Mean	350	80	41
Median	355	95	43

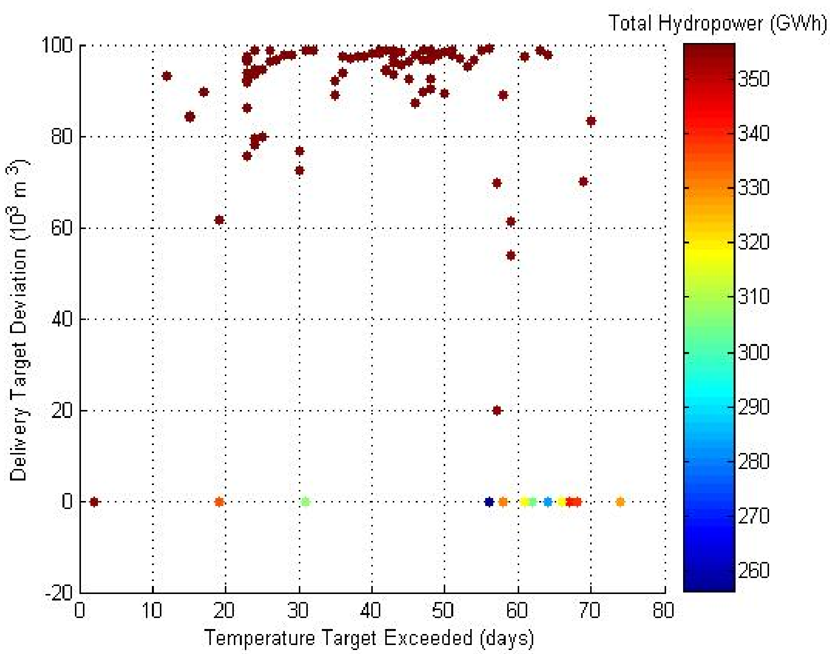

Figure 5.17: Year 2005 June – November Temperature Target Exceedance and Delivery Target Deviation Tradeoffs

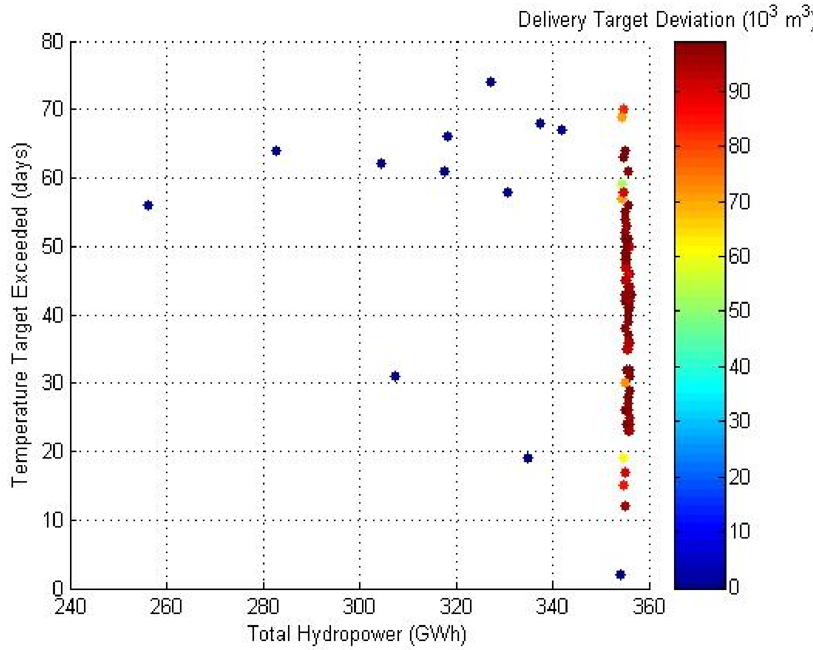

Figure 5.18: Year 2005 June – November Total Hydropower and Temperature Target Exceedance Tradeoffs

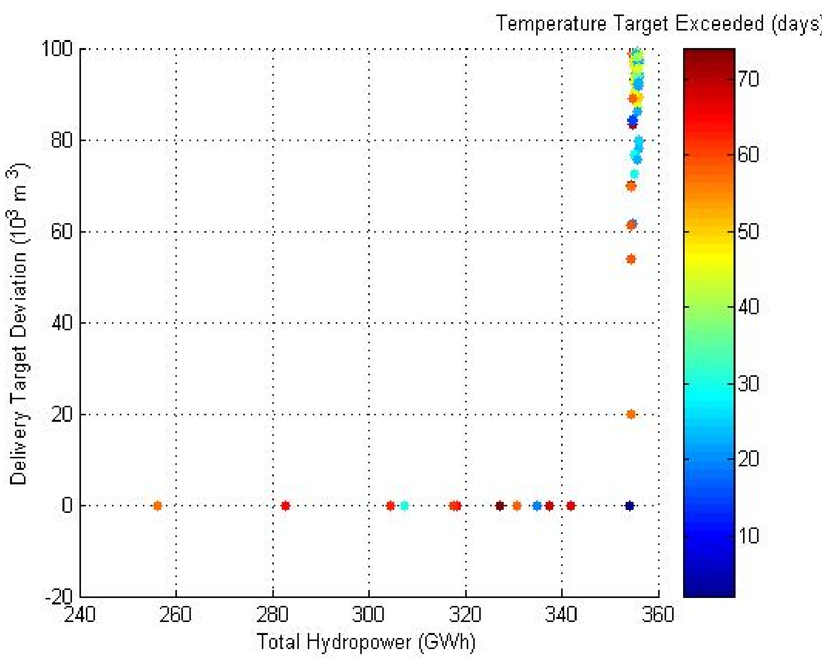

Figure 5.19: Year 2005 June – November Total Hydropower and Delivery Target Deviation Tradeoffs

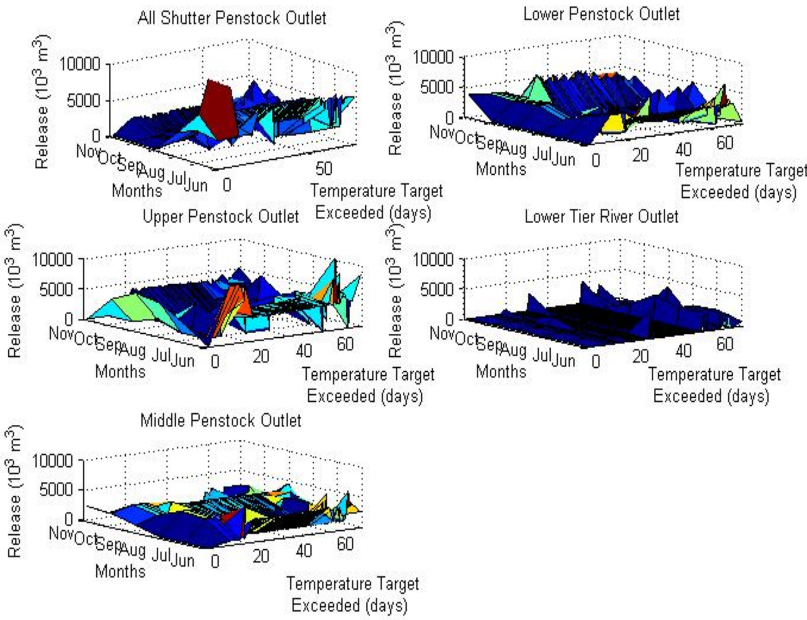

Figure 5.20: Year 2005 Non-Dominated Total Hydropower Solutions by Reservoir Outlet Release Location

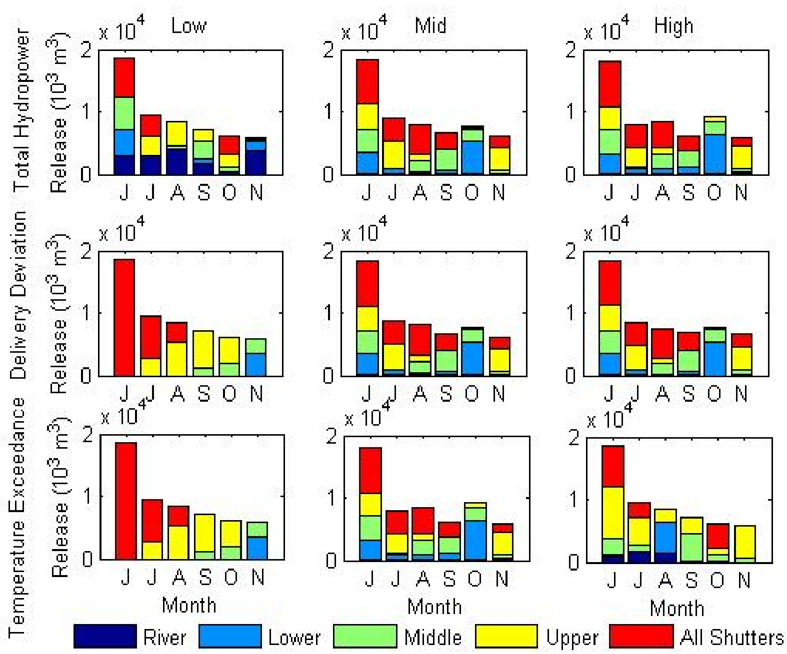

Figure 5.21: Year 2005 Release Policies (From Low to High Performance Fitness Left to Right)

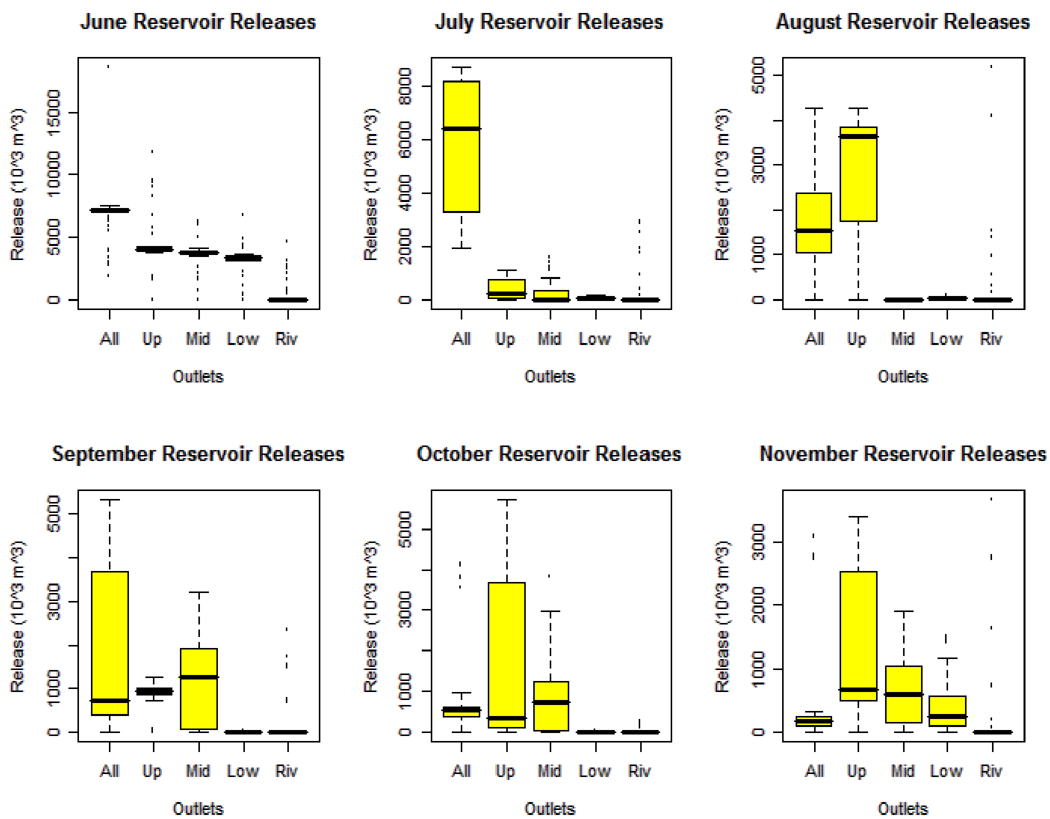

Figure 5.22: Year 2005 Evaluation of Monthly Release by Outlet

6. SENSITIVITY ANALYSIS

Sensitivity results indicate areas of further investigation or model refinement and provide insight into the performance of the linked modeling packages. The parameters examined complement the presented results and can supplement decision making. The first analysis evaluated DLM sensitivity using root mean square error (RMSE) for the temperature simulations compared to eleven field observations. The second analysis examined several key parameters that influence the development of the optimal solution set from the NSGA-II model. These were also investigated based on comparisons of the range of objective function performance metrics (due to the potentially unique solution sets from the random selection processes).

6.1 DLM Sensitivity

This sensitivity analysis explored a select set of parameters used in the calibration of the DLM and were quantified using RMSE. The equation for the temperature RMSE is:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left[(t_i^* - t_i)^2\right]}{N}} \tag{6.1}$$

where for a set of observations t_i^* is the observed temperature at a specific elevation i, t_i is the simulation temperature for a given elevation, and N is the total number of observations. The RMSE quantifies the error between the observed temperature and the simulated temperature within the reservoir in a given time period.

The temperature simulation sensitivity analysis examines parameters listed in Table 6.1. In addition, an evaluation is made to examine responses at different elevations within the reservoir and by field observation to determine both spatial and seasonal variability. Ranges of variability were selected based on suggested literature values for parameters (Fleenor, 2005).

Both the spatial discretization and light attenuation in Figure 6.1 appear most sensitive to parameter variation. This indicates that as the minimum spatial discretization is increased the vertical densities are less refined and yield less accurate temperature profiles. The temporal discretization of the DLM model is dynamically adjusted and reported daily by default, therefore no parameter was available to explore shorter time steps. Light attenuation, also illustrated in Figure 6.1, appears most sensitive at 0.2 m or less. The sediment drag and Kelvin-Helmholz billowing coefficients seem to be less responsive to parameter variation in the ranges explored.

The remaining sensitivity parameters, shear efficiency coefficient, unsteady effects coefficient, wind stirring coefficient and convective overturn coefficient examined

Table 6.1: Base DLM Simulation Model Parameter Values

Parameter	**Value**	**Units**
Spatial discretization	1	meters
Light attenuation	0.50	meters
Sediment drag coefficient	0.02	Unitless
Kelvin-Helmholz billowing coefficient	0.30	Unitless
Shear efficiency coefficient	0.20	Unitless
Unsteady effects coefficient	0.51	Unitless
Wind stirring coefficient	1.23	Unitless
Convective overturn coefficient	0.10	Unitless

in Figure 6.2 remain relatively unchanged for the ranges tested. Figure 6.3 examines the spatial location RMSE and indicates the greatest temperature deviation from observed is at 25 m above the bottom of the reservoir. This corresponds to the lowest temperature shutter location. The greatest seasonal error, in Figure 6.4, appears to be in late October 2001 and late November 2001. Weak stratification in the reservoir might prevent the simulation from accurately capturing the physical process during November.

6.2 NSGA-II Sensitivity

A similar evaluation was completed to assess the sensitivity of results to optimization algorithm parameters. The algorithm performance was evaluated using metrics which measure (1) the proximity of the non-dominated solution set to an optimal solution, (2) the spacing of the solutions or decisions, and (3) the full spread of the solution set. These metrics shown below were evaluated using the year 2001 application.

The Euclidean distance between a solution and the Pareto optimal solution is found using the Generational Distance (GD) metric in equation (6.2) (Van Veldhuizen, 1999). Although the true Pareto optimal solution (P^*) unavailable for the application, a surrogate solution is used to compare with alternative solutions (see Table 6.2 for more details). The distance evaluation, d in equation (6.3), compares the objective solution distance between f_m and the closest Pareto optimal solution $f_m{}^*$.

$$GD = \frac{\left(\sum_{i=1}^{|Q|} d_i^p\right)^{\frac{1}{p}}}{|Q|} \tag{6.2}$$

$$d_i = \min_{k=1}^{|P^*|} \sqrt{\sum_{m=1}^{m} \left(f_m^{(i)} - f_m^{*(k)}\right)^2} \tag{6.3}$$

Where:
GD = Generational Distance
Q = solution set

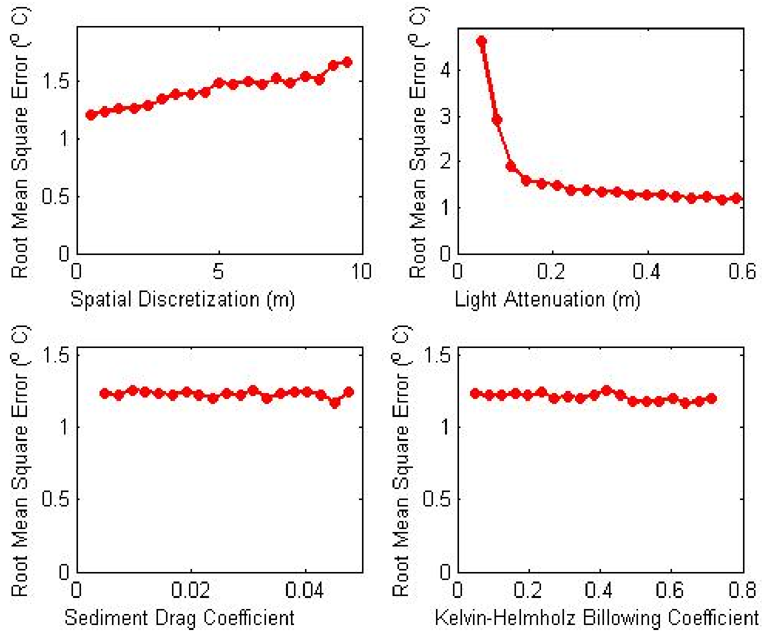

Figure 6.1: DLM 2001 Sensitivity Tests: Model Parameters and Physical Coefficients

P^* = Pareto optimal solution set
p= objectives
d = Euclidean distance between solutions in set Q and nearest member of P^*
f = objective function value from solution set Q
f^*= objective function value from solution set P^*
i = member of Q
k = member of P^*
m = objective function

Solution spacing, introduced by Schott (1995), is found using equation (6.4) and measures the relative distance between consecutive solutions and describes the diversity of the solution set. Unlike equation (6.2), this metric uses neighboring non-dominated solutions within the same solution set for comparison and not the Pareto solution in equation (6.5).

$$S = \sqrt{\frac{1}{|Q|}\sum_{i=1}^{|Q|}\left(d_i - \overline{d}\right)^2} \tag{6.4}$$

$$d_i = \min_{k \in Q \wedge k \neq i} \sum_{m=1}^{M} \left|f_m^i - f_m^k\right| \tag{6.5}$$

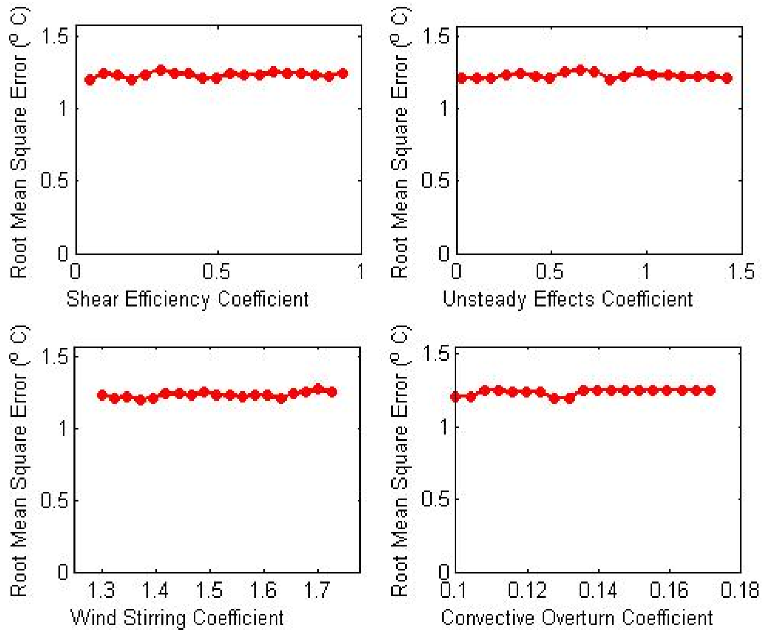

Figure 6.2: DLM 2001 Sensitivity Tests: Physical Coefficients

$$\overline{d} = \sum_{i=1}^{|Q|} \frac{d_i}{|Q|} \tag{6.6}$$

Where:
S = spacing metric
Q = solution set
d = relative distance measure between consecutive solutions
$\overline{d}$ = mean distance measure
f = objective function value from solution set Q
i = member Q
k = all other solutions of Q not equal to i
m = objective function

The solution set's maximum spread is also calculated by quantifying the length of the hyper-cube diagonal in three-dimensional space (equation (6.7)) (Zitzler, 2000).

$$D = \sqrt{\frac{1}{M}\left(\max_{i=1}^{|Q|} f_m^i - \min_{i=1}^{|Q|}\right)^2} \tag{6.7}$$

Where:
D = spread metric
Q = solution set
f = objective function value from solution set Q

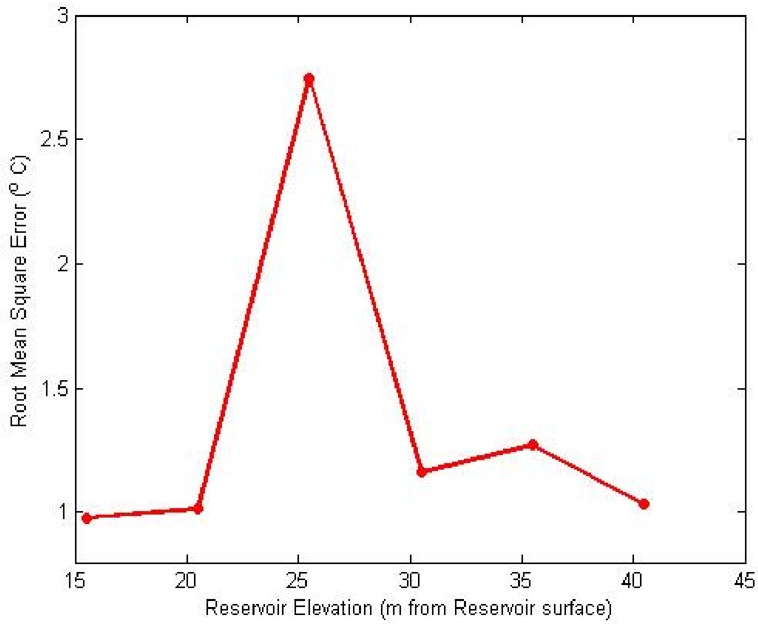

Figure 6.3: DLM 2001 Sensitivity Tests: RMSE by Location

i = memeber of Q
m = objective function
M = number of objectives

The NSGA-II sensitivity evaluation listed in Table 6.2 illustrates the comparative performance of the non-dominated solutions. Solution values (f) were normalized prior to evaluation to avoid large fluctuation in the comparison distances as recommended (Deb, 2001). In lieu of the Pareto optimal solution set, a base sensitivity run was selected for year 2001 scenario using twenty-four decision variables. All sensitivity runs include a population of 100 individuals, 450 generations, crossover probability of 90% and mutation probability of 1 in 24 (unless modified for evaluation). The performance of the objectives with a smaller population appear to have the greatest absolute change in the generational distance (or deviation from the base solution) of 0.211. The least change in the generational distance metric is with a run with the greatest number of generations (0.085). The best performance in spread from the base, a decrease of 2%, is also the run with the greatest number of generations. The best performance of spacing (a decrease of 40% from the base) is observed with the increase of tournament contestants. Other parameters such as crossover pool size, distribution and mutation index appear to have some sensitivity on the performance metrics, however all solution sets are influenced by the random generation of the initial population set and are susceptible to non-unique solutions. Additional sensitivity analysis could fix the entire initial population to eliminate this source of variability.

The Figure 6.5, Figure 6.6, and Figure 6.7 illustrate the progression of the

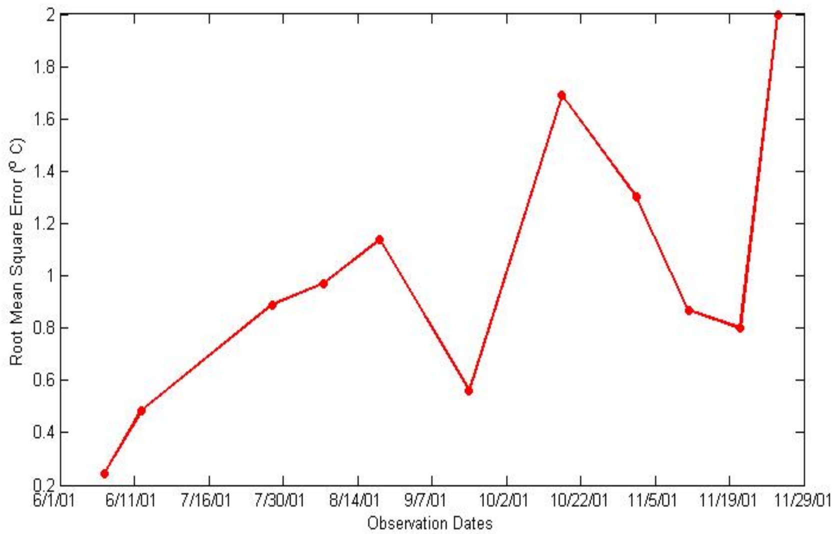

Figure 6.4: DLM 2001 Sensitivity Tests: RMSE by Season

objective function performance as the algorithm seeks the optimal solution set. The generational, spacing, and spread metrics seem to fluctuate around a mean value of 0.130, 0.103, and 5.99 respectively. Despite the anticipation that metrics would exhibit a stronger trend as the generations increased, it appears the objective functions performances are somewhat consistent over each successive generation. The sensitivity to the crowding distance infinite boundary assumption, seed parameters, crossover probability, mutation probability, and non-dominated decision diversity were not examined and is left for future investigation.

6.3 Model Limitations

Although models are used to gain insight into the complex nature of natural and anthropogenic systems, they are imperfect replications of reality. Several simulation model, optimization model, and the application limitations are identified. These limitations influence the solutions presented and are discussed to provide greater insight for interpreting the results.

6.3.1 Simulation and Optimization Model Limitations

Simulation models such as DLM used to predict reservoir and release temperatures have limitations in two general areas, assumptions made to simplify the physical processes and representative inputs to the system. The DLM model is based on the assumption of one-dimensionality. This could cause problems if horizontal convection in the lateral and longitudinal occurs more rapidly than the vertical advection. In addition, the vertical density estimation may break down if subjected to conditions outside of the range of calibration. This is due to imperfect knowledge of the processes

Table 6.2: NSGA-II Sensitivity Analysis Performance Metrics

Parameter	**Base**	**Variation**	**Generational Distance**	**Spacing**	**Spread**
Base	N/A	N/A	0.00	0.103	6.396
Population	100	50	0.211	0.180	6.121
Population	100	200	0.120	0.110	6.008
Tournament (contestants)	2	4	0.100	0.066	6.048
Crossover pool size	50	75	0.089	0.097	6.054
Crossover distribution index	20	10	0.124	0.102	6.131
Mutation index	20	10	0.118	0.094	6.112
Generation	450	1-1000	0.085-.176	0.072-0.195	5.80-6.25

that drive the vertical interactions. Two additional areas of suspected limitation are time periods when reservoir overturn occurs (weak stratification) and when biological processes occur. The former may occur when the Wedderburn number and the Lake Number are small and may invalidate the one-dimensionality assumption usually during the winter season (Fleenor, 2005), and may have happened in the 2001 November simulation. The latter issue may be because this simulation did not describe a comprehensive nutrient analysis for biological growth. Simulated epilimnion temperature deviation to historical in July for both the 2001 and 2005 time periods is suspected to have insufficient algal bloom information. Other process limitations, not discussed here, seemed to have less significant effects on the reservoir temperature simulation, but are nevertheless limitations of the model.

Available input information also limits model accuracy. For this application of the DLM, data was nearly complete for both the 2001 and the 2005 time frames. With the exception of long wave radiation (percent of sky not covered by clouds was used instead) all data sources were collected at the desired time step or were correlated using regression relationships (see Appendix F for input details). Evolutionary algorithms are promising tools to use for difficult real world problems, but they also have limitations. A practical limitation of applying evolutionary algorithms for environmental engineering applications is run time. Evolutionary algorithm optimization solutions typically require thousands of simulations which can be a time consuming complex models. Other limitations can include the calibration of selection, cross-over or mutation parameters. This also adds to the number of simulation executions because these parameter values can not be chosen a priori (Dorn and Ranjithan, 2003).

Another limitation to multi-objective optimization using an evolutionary algo-

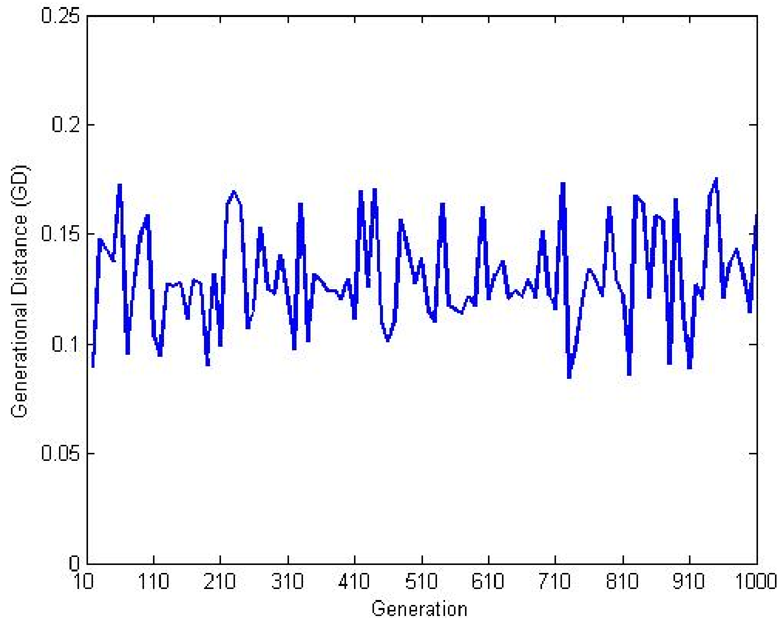

Figure 6.5: NSGA-II Generational Distance Sensitivity

rithm is the assumption of the accuracy of the Pareto optimal front. Veldhuizen and Lamont (2000) point out for real world application, a Pareto solution may or may not be optimal due to the limitations of the number of objective functions chosen and the finite computational capabilities of computers. Nevertheless, practitioners routinely make this assumption to accept the model output as the true Pareto optimal.

Several aspects of multi-objective optimization evolutionary solution techniques also make their use a challenge. Deb (2001) identifies several issues that should be considered and researched in more depth. One issue is the communication of results. This is especially problematic with more than two objectives. Difficulties may also occur with convergence, diversity of solution set, convexity, discontinuity, and non-uniformity. Also (Deb, 2001), constrained problems have a narrower spread of solutions. Depending on the niching scheme or search method, decision variable or objective space, some algorithms may not reveal all desired solution information. In addition, having more than two objectives may be problematic if populations only generate an elite solution and prevent diverse new solutions in future generations (Deb, 2001).

6.3.2 Application Specific Limitations

The results of this application to Folsom Reservoir are also limited by simplifications and are discussed in each of the three objective categories, water supply delivery, hydropower generation, and downstream temperature control. First, optimization release decisions for water supply delivery are evaluated based on the total six month

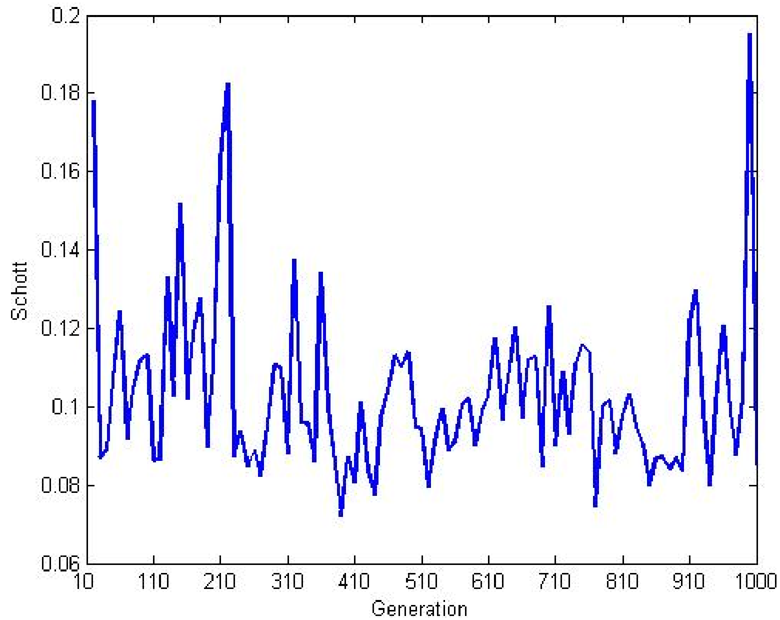

Figure 6.6: NSGA-II Spacing (Schott) Sensitivity

delivery quantity, not the monthly quantity targeted. This could affect delivery obligations and the thermal stratification of the reservoir if water is not released as forecasted. Because no criteria constrains the specific month in which water is released from the reservoir it is conceivable that a perfect evaluation could be reached by releasing all the water in only a few months and not at all in others. However, a cost to water supply delivery could be a benefit to downstream temperature control, as is seen in the year 2001 scenario. In addition, the municipal delivery assumption may affect the quantity of water available at specific thermoclines, and depends on the particular temperature pumped by the municipality. Last, modifications to the release configuration are allowed only at the beginning of each of the six months, on occasion mid-month modification may be desired and may limit the flexibility of the downstream temperature control. The greatest impacts on the water supply delivery objective seem to be related to such timing issues.

The second objective, hydropower generation is evaluated based only on energy maximization, no target energy is specified. Due to this assumption, the generation of hydropower will tend to drive the location of release, i.e. from the penstock rather then the river outlet. In addition, the simulation of hydropower does not consider the subtleties of the generation process such as peaking generation, maintenance, and seasonal price variations. This could affect the total power generated reported in the optimal solution set.

The downstream temperature control objective, the third and last objective, is limited by a target temperature rather than a simulated downstream temperature. Although the target release temperature is conservative, it is conceivable that cooler

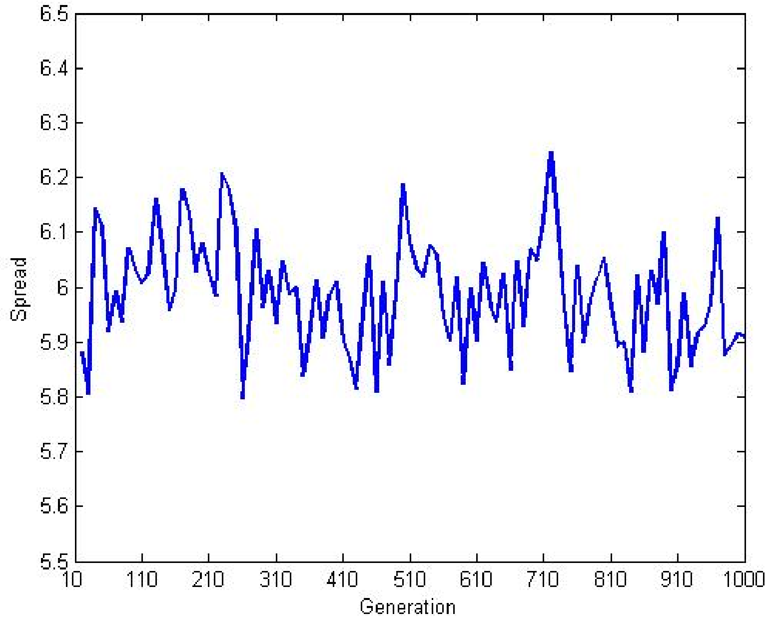

Figure 6.7: NSGA-II Spread Sensitivity

reservoir release locations are prematurely used leading to premature depletion of cold water at higher shutter elevations. This limitation could artificially reduce hydropower generation, or maintain the downstream river temperature at a cooler than optimal temperature.

7. CONCLUSIONS AND RECOMMENDATIONS

The information presented demonstrates the linkage of a temperature model, simulating reservoir and release temperatures, and a multiple objective optimization algorithm for reservoir release decision analysis. The Folsom Reservoir model development and analysis aimed to capture two areas overlooked:

1. reservoir evaluation from a multiple objective perspective resulting in a set of optimal solutions and
2. quantification of the associated tradeoffs.

It is anticipated that water management, power generation, and wildlife and fishery agencies are interested in the tradeoffs eatimated with multi-objective optimization for resource management decision making. Recommendations are also offered for further study to address some of the imperfections and simplifications of the model development.

7.1 Conclusions

The coupled temperature simulation and multi-objective optimization results presented demonstrate:

1. Initial reservoir conditions and year type influences (for year 2001 and year 2005) yield different non-dominated release policies for the months June-November.
2. For the year 2001 conditions, a generalized tradeoff was found between hydropower generation and temperature target exceedance. Temperature target exceedance days increase exponentially as hydropower generation increases, from use of the lower river outlets which bypass the turbines.
3. For the year 2001 conditions, there is some advantage to forego delivery target release, but not for the year 2005 conditions.
4. For both years 2001 and 2005 conditions, multiple outlet blending policies appear to be desirable for the June – November period.
5. The year 2001 historical release configuration was not a non-dominated solution, however the year 2005 was.
6. The temperature simulation is most sensitive to spatial discretization and light attenuation.

7. The temperature simulation tradeoff for increased accuracy using the finer spatial discretization is increased computation time.

7.2 Recommendations for Future Study

The models and results could be further refined to enhance results interpretation or decision making by incorporating the following recommendations:

1. Perform uncertainty analysis on key sets of inputs that appear to have influence on the water temperature, such as Monte Carlo analysis on initial reservoir conditions, water supply demands, solar radiation, etc. Both year 2001 and 2005 appear to have similar metrological and precipitation inputs. However, recent studies (California Department of Water Resources, 2006) have indicated future conditions may differ. This information could assist in the assessment of reservoir release decisions for uncertain future climatic conditions.

2. Refine the performance evaluators of the optimization based on the deviation of water supply delivery per month instead of six month period to address the timing of water supply delivery.

3. Evaluate the performance of the optimization based on a variable temperature target downstream or hydropower target. Fishery agencies may have year type or biological influences that may alter the fixed temperature target of 15.5°C. Hydropower could also be specified as a target or hydropower revenue maximization rather than a global energy maximization.

4. Enhance the detail of meeting the downstream temperature. This would include a simulation of the temperature as it travels downstream from the reservoir to the temperature control point at Watt Avenue Bridge.

5. Refine the performance of the DLM model particularly in July and November when biological activity and reservoir de-stratification is suspected.

6. Increase the release and location decision variables to simulate a TCD capable of automation (with daily alterations) and with more shutter openings.

7. Refine the municipal water supply delivery from Folsom Reservoir with a dynamic temperature dependent withdraw.

8. Incorporate and define criteria for additional objectives such as recreation or hydropower revenue. Hydropower peaking, seasonal demand, and varying prices may favor hydropower earlier in the season rather then an objective with uniform priority over the six month period as presented here.

9. Investigate in further detail the sensitivity of the optimization parameters.

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APPENDIX

A. EVOLUTIONARY ALGORITHMS AND NON-DOMINATED SORTED GENETIC ALGORITHM (NSGA-II) OVERVIEW

The following excerpt is an overview of evolutionary algorithms and the NSGA-II algorithm (Field and Lund, 2006):

Pareto optimality is the fundamental reason to seek a set of solutions in multi-objective optimization. Pareto optimal or non-inferior "fronts" are objective vectors in which no component can be improved without diminishing the status of at least one other component. This means a Pareto optimal front set of solutions are the best set for one or more conflicting objectives over a wide range of decision alternatives. Two spaces are formed to determine a Pareto optimal solution, the decision space and objective space (Deb, 2001). Decision space represents all decision variables of the optimization that satisfy the constraints of the multi-objective problem. Objective space represents all solutions of the objective function in the m-dimensional space of m objectives. The best solution of a multi-objective problem resides within the objective space, called the Pareto optimal or non-dominated set as described by Miettinen (1999): "A objective vector $z* \in Z$ is Pareto optimal if there does not exist another objective vector $z \in Z$ such that $z_i \leq zi*$ for all $i - 1, \ldots, k$ and $z_j < z_j*$ for at least one index j; or equivalently, $z*$ is Pareto optimal if the decision vector corresponding to it is Pareto optimal." In application, the final solution is selected from the non-dominated set by decision makers, informed of trade-offs among the system's objectives by the model results. Discussions on local and global optimality, tests and proofs are left to Miettinen (1999) and Deb (2001).

NSGA-II is an elitist multi-objective evolutionary algorithm which seeks Pareto optimal objective function fronts. A pool of solutions are "selectively bred", in a set number of generations, for the desired objectives. The algorithm has four procedures (Deb, 2001):

1. compare parent and offspring populations
2. select the next parent generation
3. a crowding-sort procedure
4. generate next offspring generation

The algorithm is initialized with a randomly selected set of decision variables as a parent population. The first offspring population is generated using genetic operators (selection, crossover and mutation) based on members from the parent population. The fitness of each member (evaluation of the objective functions) is then calculated. Then both the parent and offspring population are joined and sorted. This sort is based on non-dominance, where the fitness of a superior member is ranked higher than those whose fitness can be outperformed by another member. This step provides a direct opportunity for the parent's traits to compete for a spot in the next generation. The best members, or the elite, are given priority positions in the next generation which prevents performance degradation of the population. If elite members do not fill all available positions in the next generation, the remainders are selected based on non-dominance criteria and proximity. Crowded solutions prevent the discovery of multiple optima solutions, solutions that are close in proximity are discouraged by selecting more evenly dispersed solutions for the next generation. This sequence of filtering solutions is terminated after a specified number of generations, yielding the Pareto optimal fronts (Deb, 2000).

B. DLM CALIBRATION AND TESTING: RESERVOIR PROFILES

DLM Calibration was performed June 1, 2001 through November 30, 2001 for Folsom Reservoir using eleven recorded temperature profiles measured at Folsom Dam. The blue open circles, in Figures B1 through B6, represent observed temperature points at a corresponding depth in the reservoir. The red solid line represents the DLM simulated temperature. Figure B.1, Figure B.2, and Figure B.3 illustrate the performance of the calibration of the model comparing recorded and simulated temperature profiles beginning in June 2001 and ending in November 2001. Figure B.4, Figure B.5, and Figure B.6 illustrate the testing of the calibrated DLM model from June 1, 2005 to November 30, 2005.

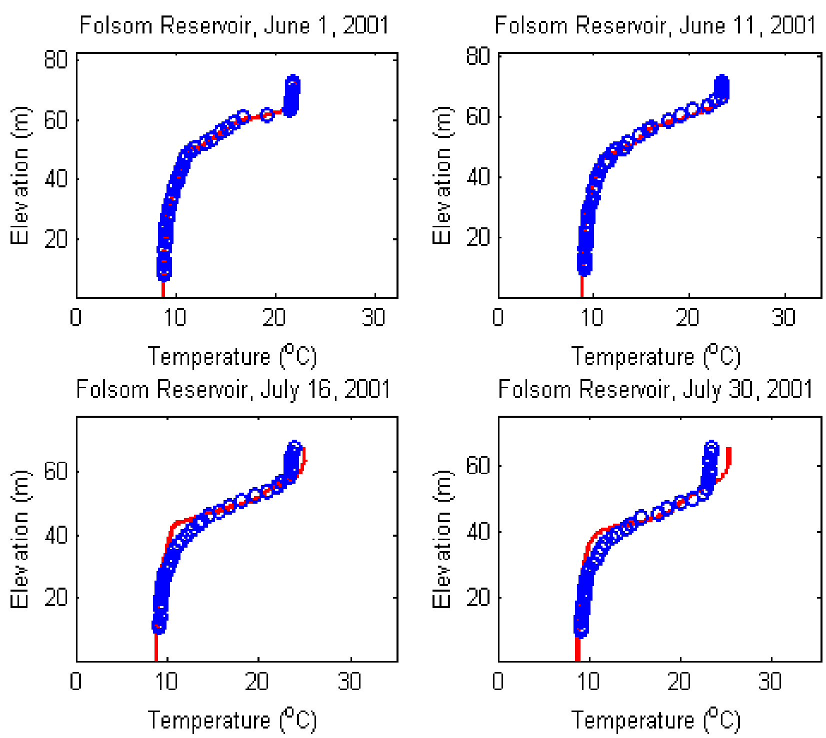

Figure B.1: DLM Calibration Temperature Profiles for Folsom Reservoir June 2001 through July 2001

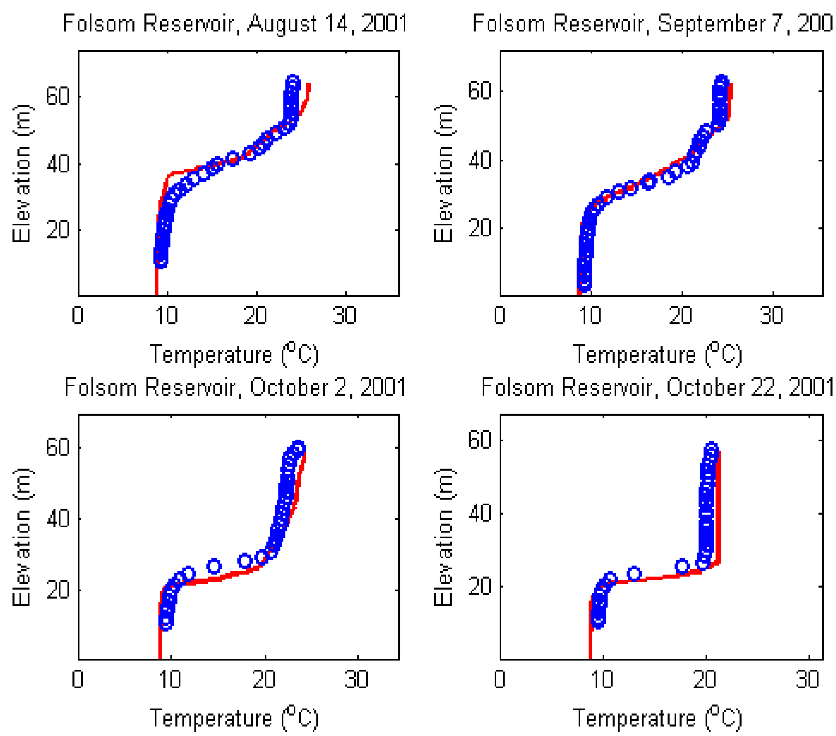

Figure B.2: DLM Calibration Temperature Profiles for Folsom Reservoir August 2001 through October 2001

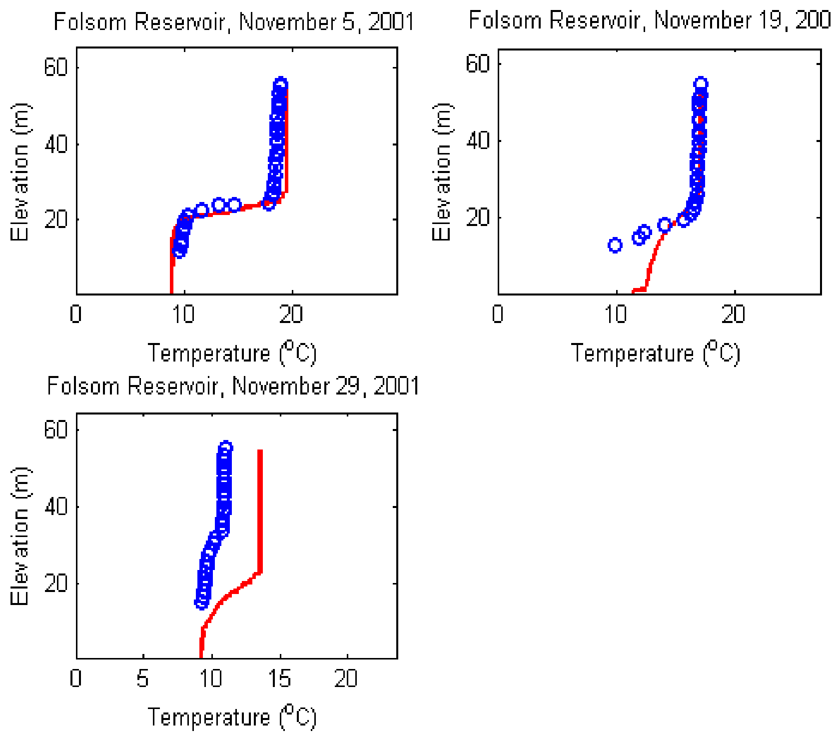

Figure B.3: DLM Calibration Temperature Profiles for Folsom Reservoir November 2001

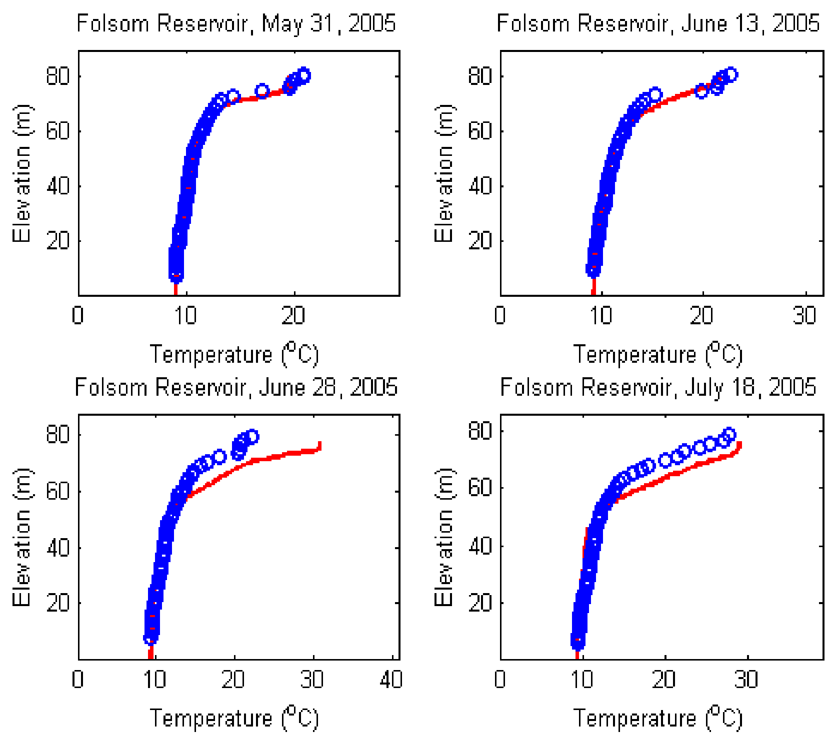

Figure B.4: DLM Testing Temperature Profiles for Folsom Reservoir June 2005 through July 2005

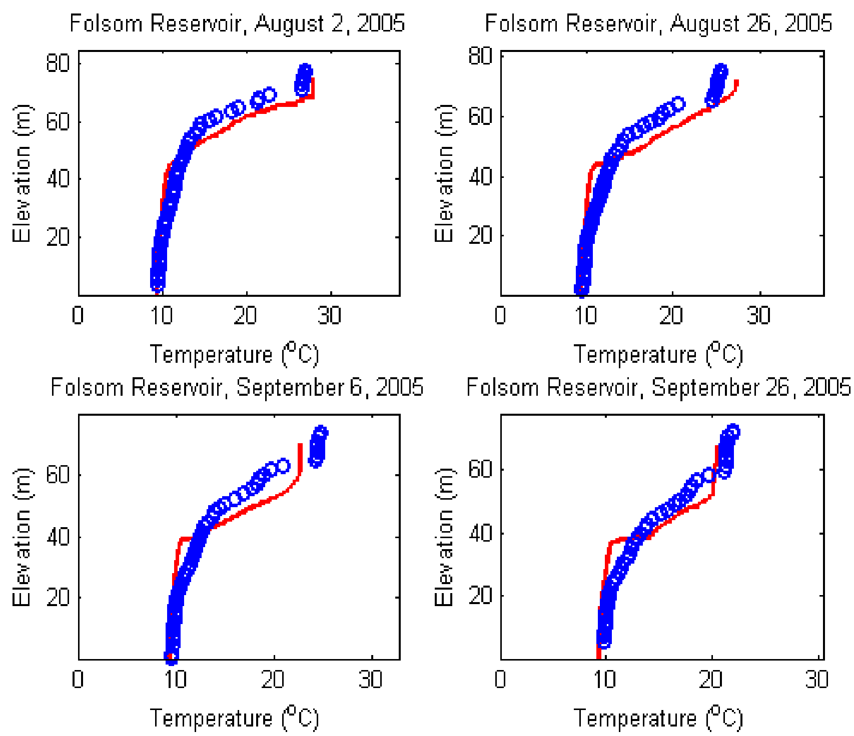

Figure B.5: DLM Testing Temperature Profiles for Folsom Reservoir August 2005 through September 2005

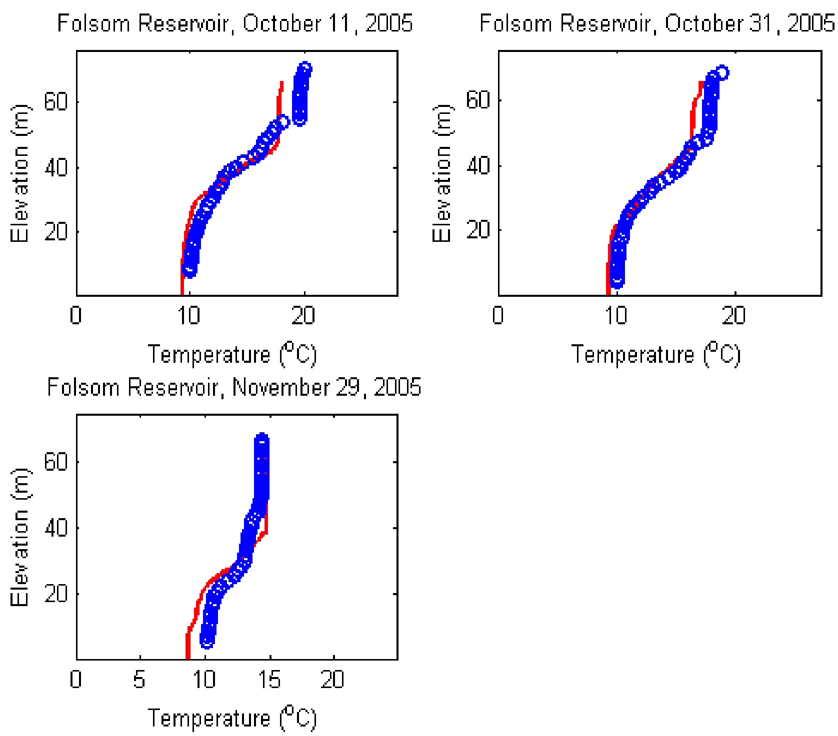

Figure B.6: DLM Testing Temperature Profiles for Folsom Reservoir October 2005 through November 2005

C. MODEL INPUTS AND APPLICATION ASSUMPTIONS

Table C.1: DLM Parameter Details Part 1

Category	**Type**	**Units**	**Description**	**Range**	**Source**
Initial Conditions	Reservoir Volume	m^3	Historical volume (2001: 858 million m^3 and 2005: 1.18 billion m^3)	1-Jun	CDEC (FLD Station)
Initial Conditions	Reservoir Elevation	m	Historical elevation (2001: 134 m msl and 2005: 142 m msl)	1-Jun	CDEC (FLD Station)
Initial Conditions	Reservoir Temperature Profile	°C	Historical vertical reservoir temperatures recorded at Folsom Dam.	1-Jun at 1.5 m intervals	(Yaworsky, 2005)
Meteorology	Short Wave Radiation	kJ/m^2	Historical data.	1-Jun to 30-Nov	CIMIS (Davis Station)
Meteorology	Cloud Cover	Percent of sky not covered by clouds	Historical data.	Same as above	NWS (Sacramento Executive Airport WBAN: 23232)
Meteorology	Air Temperature	°C	Historical data.	Same as above	CIMIS (Fair Oaks Station)
Meteorology	Relative Humidity	Percent	Historical data.	Same as above	CIMIS (Fair Oaks Station)

Table C.2: DLM Parameter Details Part 2

Category	**Type**	**Units**	**Description**	**Range**	**Source**
Meteorology	Wind Speed	m/s	Historical data.	Same as above	CDEC (FLD Station)
Meteorology	Precipitation	mm	Historical data.	Same as above	CIMIS (Fair Oaks Station)
Hydrology	Upper American River Inflows	m^3/day	Calculated historical Folsom inflow data (from CDEC station: FOL) is disaggregated to the North Fork and South Fork of the American River based on flow relationships from 1967-1978 excluding year 1977. Information provided by Reclamation (statistical fitness was unavailable).	Same as above	CDEC (FOL Station) and (Yaworsky, 2005)
Temperature	Upper American River Inflow Temperature	°C	Historical data. Missing data on the South Fork of the American River is found using a correlation with the North Fork based on data from 1999-2001. Correlation relationship has a R^2 value of 0.95.	Same as above	(Yaworsky, 2005)

Table C.3: DLM Parameter Details Part 3

Category	**Type**	**Units**	**Description**	**Range**
Water Demands	Total Folsom Reservoir water demands	m^3/day	A six month 90% hydrology exceedance forecast is used to estimate water demands. Total monthly demand is disaggregated to a constant flow for all days in the month. Municipal water supply (which is also temperature selective) is assumed to exit the dam outlet works rather than from within the reservoir to simplify the problem. Municipal demands are included in the monthly demand forecast. Estimated requirements for downstream regulatory standards such as minimum in-stream flows and Sacramento-San Joaquin Bay Delta water quality requirements are also included in the monthly demand forecast.	June-November
Operation	Temperature Shutter Configuration	per month	Due to initial reservoir volume conditions, four outlets are assumed available: upper, middle, and lower penstock shutters, and the lower tier river outlet. Outlet adjustments are assumed once per month.	Same as above

Table C.4: DLM Parameter Details Part 4

Category	**Type**	**Units**	**Description**	**Range**	**Source**
Operation	Hydropower Generation	kWh	Hydropower generation is assumed when water flows through any of the upper, middle, or lower penstock shutters. Hydropower is not generated when water is released from the lower tier river outlet. No adjustment is made for potential operational or maintenance generation outages.	Same as above	
Regulatory Constraints	River temperature at Watt Bridge	°C	The reservoir target release temperature is 15.5 °C.	Constants	(Yaworsky, 2005)
Spatial Discretization	Maximum Vertical Layer Depth	m	A coarse discretization (2 meters) was used to expedite run time. Discretization sensitivity was verified.	Constants	
Biological Parameters	Algal related parameters	Various	Values were calibrated (within the range of literature reported values).	Constants	

Table C.5: NSGA-II Parameter Details

Type	**Units**	**Description**	**Source**
Population Size	Numbers of individuals	100	User specified
Generations	Numbers of iterations	1500	User specified
Decision Variable Constraints	m^3	0-5000 m^3	User specified
Sort	NA	Non-Dominated Sort	(Deb et al., 2002)
Crowding Distance	NA	Euclidian distance between individuals on the Pareto front, based on all objectives	(Deb et al., 2002)
Selection	NA	Tournament Selection = 2. Pool Size = initial population/2	(Deb et al., 2002)
Crossover probability	Percent	90	(Seshadri, 2006)
Crossover index	NA	Simulated Binary Crossover,$\eta_c = 20$	(Seshadri, 2006)
Mutation probability	Percent	1/decision variables	(Seshadri, 2006)
Mutation index	NA	Polynomial Mutation, Uniformly Distributed $\eta_m = 20$	(Deb et al., 2002)

D. NSGA-II/DLM LINKAGE AND OBJECTIVE CODE (MATLAB)

```
function f = evaluate_objective(x,problem)

% Function to evaluate the objective functions for
% the given input vector x. x has the decision
% variables

switch problem
case 1
f = [ ];
%% Case one not used
case 2
f = [ ];
tstep1 = 6; % is equal to release changes in 6 months
tstep2 = 30; % days per month
tstep3 = 31; % days per month.
lastday = 2005334;
dvar = 30;
targ =[1.857223554,0.935462284,0.848322242,
0.709667446,0.616704804,0.584303828]; %2005
xout=reshape(x(1:dvar),tstep1,5);
lastsim=load('folsom.txt');

%%Folsom Temperature Optimization
% find scores for each separate objective function
for i=1:tstep1
if(i<=1) %June
out=repmat(xout(i,:)*10000,[tstep3 1]);
elseif(i == 2 || i == 3 || i == 5) % July,Aug, Oct
outx=repmat(xout(i,:)*10000,[tstep3 1]);
out=vertcat(out,outx);
else %Sept, Nov
outx=repmat(xout(i,:)*10000,[tstep2 1]);
out=vertcat(out,outx);
end
end

jdays=[2005151:lastday]';
```

```
%if flow is greater than max, give it a bad score and
%don't run the WQ simulation
maxflow =(5.5516)*10000; % m∧3
sumout=sum(xout',1)*10000;
allsum = sum(sumout);
overflow = abs(allsum - maxflow);
if(overflow > 100)
f(1) = 10000; %power
f(2) = 400; %target temp
f(3) = 10000; %water delivery
else
outflow= horzcat(jdays,out);
%write out text file, input to external program
dlmwrite('folsom.out',outflow,'delimiter', '
t','precision','%7.0f');
%type folsom.out;
timenow = fix(clock);
if(timenow(1,5)== 59)
pause(61);
end
!DLM_WQ3_0.exe
% Read in results from DLM
sim=load('folsom.txt');
[row, col]=size(sim);
[rowa, cola]=size(lastsim);
if row==rowa & col==cola & sim==lastsim
%Re-run with a finer resolution
%Artificially replace with a bad solution
copyfile('folsom_artif.txt','folsom.txt');
profile = 'folsom2005151.pro';
protemp = 'savefolsom2005151.pro';
profine = 'finefolsom2005151.pro';
copyfile(profine,profile);
!DLM_WQ3_0.exe
% Read in results from DLM
sim=load('folsom.txt');
[row, col]=size(sim);
copyfile(protemp,profile);
end
jday=sim(1:row,1);
selev=sim(1:row,2);
stemp=sim(1:row,3);
lastsim = sim;
alldays = [152:333]';
[row, col]=size(alldays);
```

```
for i=1:row
send = find(jday==alldays(i,1),1,'last');
ie(i,1)=send;
end
[row, col]=size(ie);
for i=1:row
elev(i,1)=sim(ie(i),2);
end
% don't use outlet that does not generate power
outf=outflow(:,2:5);
outftot = sum(outf');
[row, col]=size(outftot);
ot = outftot(2:col-1)';

elev= (elev+60.96)*3.280; %convert from m to ft msl
%convert from 10^3 m^3 to cfs
outcfs = (ot*1000)/(86400*0.028317);
for i=1:row
if(outcfs(i)<0.0001)
tr(i:1) = 0;
else
tr(i:1)=10^(2.113508-0.035579*log10(outcfs(i)
/1000)+0.04750301*log10(outcfs(i)/1000)^2);
end
end
tr=tr'; %tail race
gh=elev-tr; %gross head
ef=((0.92854*gh)-16.282)'; %efficiency kWh/acre-ft
kwh=ef*(outcfs*0.00198347*1000); %kilo watt hours
f(1) = -(kwh/1000000)*0.955; %power in GWh

outf=outflow(2:end-1,2:6);
outftot = sum(outf')';
target=15.5; %60 degree F

[row, col]=size(alldays);
for i=1:row
sbeg = find(jday==alldays(i,1),1,'first');
send = find(jday==alldays(i,1),1,'last');
is(i,1)=sbeg;
ie(i,1)=send;
end

[simrow, simcol]=size(sim);
for i=1:row
```

```
in1=find(61.5 < sim(is(i):ie(i),2),1);
while(sim(in1+is(i)-1,2)>61)
in1 = in1-1;
end
if(in1 > 1) %if elevation is found then pull out temp
ind1=in1+is(i)-1;
otemp=sim(ind1,3);
ft(i,1)=(outflow(i,2)*otemp);

saveElev(i,1) = sim(ind1,2);
saveTemp(i,1) =otemp;
saveOutF(i,1) = outflow(i,2);
else
ft(i,1)=0;
outflow(i,2)=0;

saveElev(i,1) = sim(ind1,2);
saveTemp(i,1) =otemp;
saveOutF(i,1) = outflow(i,2);
end
in2=find(49.0 < sim(is(i):ie(i),2),1);
while(sim(in2+is(i)-1,2)>49)
in2 = in2-1;
end
if(in2 > 1) %if elevation is found then pull out temp
ind2=in2+is(i)-1;
otemp=sim(ind2,3);
ft(i,2)=(outflow(i,3)*otemp);

saveElev(i,2) = sim(ind2,2);
saveTemp(i,2) =otemp;
saveOutF(i,2) = outflow(i,3);
else
ft(i,2)=0;
outflow(i,3)=0;

saveElev(i,2) = sim(ind2,2);
saveTemp(i,2) =otemp;
saveOutF(i,2) = outflow(i,3);
end
in3=find(40.0 < sim(is(i):ie(i),2), 1);
while(sim(in3+is(i)-1,2)>40)
in3 = in3-1;
end
if(in3 > 1)
```

```
ind3=in3+is(i)-1;
otemp=sim(ind3,3);
ft(i,3)=(outflow(i,4)*otemp);

saveElev(i,3) = sim(ind3,2);
saveTemp(i,3) =otemp;
saveOutF(i,3) = outflow(i,4);
else
ft(i,3)=0;
outflow(i,4)=0;

saveElev(i,3) = sim(ind3,2);
saveTemp(i,3) =otemp;
saveOutF(i,3) = outflow(i,4);
end

in4=find(24.0 < sim(is(i):ie(i),2), 1);
while(sim(in4+is(i)-1,2)>24)
in4 = in4-1;
end
if(in4 > 1)
ind4=in4+is(i)-1;
otemp=sim(ind4,3);
ft(i,4)=(outflow(i,5)*otemp);

saveElev(i,4) = sim(ind4,2);
saveTemp(i,4) =otemp;
saveOutF(i,4) = outflow(i,5);
else
ft(i,4)=0;
outflow(i,5)=0;
end
in5=find(4.0 < sim(is(i):ie(i),2),1);
if(in5 >1)
ind5=in5+is(i)-1;
otemp=sim(ind5,3);
ft(i,5)=(outflow(i,6)*otemp);

saveElev(i,5) = sim(ind5,2);
saveTemp(i,5) =otemp;
saveOutF(i,5) = outflow(i,6);
else
otemp=sim(simrow,3);
ft(i,5)=(outflow(i,6)*otemp);
outflow(i,6)=outflow(i,6);
```

```
saveElev(i,5) = sim(in5,2);
saveTemp(i,5) =otemp;
saveOutF(i,5) = outflow(i,6);
end


oftest(i,1) = sum(outflow(i,2:6));
if(oftest(i) < 0.0001)
fintemp(i,1)=500;
else
fintemp(i,1)=sum(ft(i,:))
/sum(outflow(i,2:6));
end
end

degday = find(fintemp > target);
[over, under]=size(degday);
f(2)= over; %temperature target

[row, col]=size(targ);
totarg = 0.0;
for i=1:col
totarg = totarg+(abs(targ(i)
-sum(xout(i,:)',1)));
end
f(3)=totarg; %delivery target
end
end
```

E. MODIFIED RANDOM SEED GENERATOR CODE (MATLAB)

```
%Random Seed generator
for z=1:100
targ = [1.857223554,0.935462284,0.848322242,
0.709667446,0.616704804,0.584303828]';
%outlets = 4;
outlets = 5;
%random numbers from 0 - 1
mon = rand(6,(outlets-1))*.5;
[row2, col2] = size(mon);
%random numbers from 1 - 4
a = 1;
b = outlets;
x = a + (b-a) * rand(1,6);
w = round(x);
[row, col] = size(x);
for i=1:6
diff(i) = targ(i)-sum(mon(i,:));
end
for i=1:col
count=1;
while diff(i)< 0 | count == 100
for j=1:col2
mon(i,j) = max(mon(i,j)+diff(i)/(outlets-1),0);
end
diff(i) = targ(i)-sum(mon(i,:));
if(abs(diff(i))< 0.0000001)
diff(i) = 0;
end
count = count+1;
end
end
for i=1:row2
p=1;
for j=1:outlets
if(w(i)== j)
mon2(i,j) = diff(i);
else
```

```
mon2(i,j) = mon(i,p);
p=p+1;
end
end
end
seed(z,:) = reshape(mon2,1,(outlets*6));
end
```