OPTIMIZING INTEGRATED WATER RESOURCES MANAGEMENT: DATA, TOOLS, AND EXAMPLES

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ABSTRACT

Best utilizing water resources requires coordinating their availability and use in time and space. Required can be: spatially and temporally distributed data; simulators to predict system response to stimuli; procedures for defining management goals, constraints, and scenarios; optimizers to compute optimal management strategies; and appropriate strategy implementation techniques. Here, a strategy is a set of controllable groundwater extraction and injection rates and surface water diversions. Simulation/optimization (S/O) models couple simulators and optimizers to compute optimal strategies for posed management problems. S/O models are becoming more commonly used for policy, planning, system design, and management. For example, water planners and managers sometimes must decide how to control groundwater use to cause a favorable future and avoid serious problems. S/O models can help determine the policies, physical systems, and management strategies that can yield the best consequences. 'Best' is defined by the manager/modeler in terms of water availability, sustainability, crop production, economic, social, or environmental criteria, or combinations of those. Addressing multi-objective optimization problems and developing quantified tradeoff curves is simple with a powerful S/O model such as SOMOS. Examples demonstrate data needs and S/O model power for policy and plan development and system design and management.

INTRODUCTION

Simulation models are useful for predicting physical system response to stimuli. Stimuli can include groundwater pumping, recharge, stream diversion, return flow. Some stimuli are manageable and some are not. Determining the best values for manageable stimuli (the best management strategy) is aided by simulation/optimization (S/O) modeling. An S/O model can determine how to maximize achievement of user-specified management objectives, subject to specified restrictions. An S/O model couples: a simulation module that can predict the consequences of management; and an optimization module that can compute the mathematically best management strategy for a posed management optimization problem.

An S/O model directly computes the mathematically best (optimal) management strategy for a management problem posed by the user. For example, a pumping

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(groundwater management) strategy is a set of spatially and possibly temporally distributed rates of extracting water from an aquifer.

S/O model use differs from use of normal simulation models (here termed S models), such as MODFLOW and MT3DMS. S models predict how the modeled physical system will respond to a user-input strategy. S models are not designed to compute optimal management strategies. Using them for this requires trial and error and yields the best strategy only for simple problems. S/O models incorporate S models or surrogates to predict system responses. An S/O model is only as accurate for prediction as the S model it includes.

S/O models for simple field situations use analytical equations for simulators, and generally use classical operations research (OR) algorithms for optimization. Analytical equations are used when problem simplicity or available capabilities do not justify use of numerical (finite difference or finite element) S models. Peralta and Wu (2004) describe S/O model applications for such field scale groundwater and conjunctive water management problems. S/O models for aquifer or regional groundwater or conjunctive water planning require numerical flow S models as simulators. Peralta and Shulstad (2004) describe evaluating water policy alternatives for different hydrogeologic and legal-institutional settings.

To optimally design pump and treat (PAT) systems for remediating groundwater contamination, S/O models require numerical flow and transport models. Peralta (2001) and Peralta et al (2003) list groundwater contamination remediation examples, using the SOMOS code (SSOL, 2001; Peralta, 2003). Such a pump and treat (PAT) system might include dozens of extraction wells to remove contaminated water, before treating it.

Peralta (2001) and Peralta et al (2003) describe several direct comparisons between designs developed by S/O modeling versus designs prepared simultaneously by trial-and-error S modeling. S/O modeling always produced superior designs, usually about 20 % better, but sometimes about 50% better.

Both S and S/O models require sufficient data to allow reasonably accurate prediction of system response to management or its lack. S/O models require additional data to define management goals and constraints. Necessary information can include distributed quantitative and qualitative data of existing and potential water uses, soil, and water, and limits on acceptable values of those and other variables.
In summary, S/O models are useful for a range of groundwater and conjunctive water management settings. Here we describe four settings: (a) sites having limited field data, suitable for analytic equation simulation; (b) sites needing numerical flow modeling; (c) contaminated sites using numerical flow and transport modeling; and (d) reservoir-stream-aquifer settings needing numerical

modeling. Respectively, the four examples use the SOMOA, SOMO1, and SOMO3 modules of Simulation/Optimization Modeling System (SOMOS), (SS/OL and HGS, 2001; Peralta, 2003), and a developmental model.

Conjunctive Use Of Simple Stream-Aquifer System

This example illustrates maximizing conjunctive use of groundwater plus surface water while achieving adequate blended salinity for irrigation (Peralta, 1999). The S/O model uses analytical equations and convolution integrals for simulation and a simplex algorithm for optimization. Field data is that needed for the analytical equations. Management data is that needed for the constraints, including water quality.

A farmer extracts groundwater using one well and diverts water from one point on a stream. He wants to maximize the sum of groundwater and surface water that is delivered to his crop during a two-month period. However, to ensure that stream flow departing his farm is adequate for downstream users, he should not reduce stream flow by more than 11,000 $m^3\ d^{-1}$ (385,000 $ft^3 d^{-1}$) at the end day 30, or by more than 11,500 $m^3\ d^{-1}$ (402,500 $ft^3 d^{-1}$) at the end of day 60. The maximum capacities of the well and the diversion are each 8,000 $m^3\ d^{-1}$ (280,000 $ft^3 d^{-1}$). The most water that should be delivered to his crop is 13,000 and 16,000 $m^3\ d^{-1}$ (455,000 and 560,000 $ft^3 d^{-1}$) in months one and two, respectively.

Other hydrogeologic and spatial information (including x,y location in meters) is: stream runs from Southeast to Northwest (800, 0) to (100,1000); diversion location is at (200,858); groundwater well (0.2 m radius), is at (450, 850); hydraulic conductivity is 80 md^{-1}; Ground surface is at 45 m elevation, and potentiometric surface is initially at equilibrium at 40 m elevation; aquifer saturated thickness is 40 m.

Also, based on crop, soil, and salinity of the surface water and groundwater, for sustainability, at least 60 % of the water used during month 1 must be from the stream, and at least 48% of the total water delivered during the two months must be from the stream. The first constraint protects seeds during germination. The second causes enough leaching to prevent root-zone salinity buildup.

To determine the maximum conjunctive water use strategy, subject to constraints, one can use the SOMOA (Peralta and Wu, 2004) module of SOMOS. (SOMOA is the successor to CONJUS). In using SOMOA one would specify: Options A and B; one extraction well; one diversion; two thirty-day stress periods; upper limits of 8,000 $m^3\ d^{-1}$ in each period on pumping and diversion; 0.6 lower limit on the water quality ratio {diversion/(diversion + pumping extraction)} for period 1; 0.48 lower limit on that ratio for the two-month total; stream flow depletion upper limits of 11,000 and 11,500 $m^3\ d^{-1}$, respectively; and pumping plus diversion.upper limits of 13,000 and 16,000 $m^3\ d^{-1}$, respectively.

Table 1 shows the computed optimal conjunctive use strategy and responses of state variables. Tight constraints are groundwater pumping in month 2, stream depletion in both months, the water quality ratio for month 1, and the total season water quality ratio. Relaxing any tight constraint (for example, decreasing the required proportion of surface water) would allow the optimizer to increase total provided water.

Table 1. Optimal conjunctive use strategy and system responses (Peralta and Wu, 2004).

	Period 1	Period 2	Season Avg.
Groundwater pumping, (GP), [m^3 d^{-1}]	4,774	8,000	
Surface water diversion, (SD), [m^3 d^{-1}]	7,001	4,573	
Stream flow depletion, [m^3 d^{-1}]	11,000	11,500	
Total delivered water, GP + SD, [m^3 d^{-1}]	11,774	12,573	12,174
Water quality ratio, {SD/(SD + GP)}	0.6	0.36	0.48

Aquifer Sustained Yield Planning With Stream Depletion Constraints

This example emphasizes maximizing sustainable groundwater use without harming existing ecosystems and legal surface water rights (Das, 2002; Das et al, 2004). The employed S/O model simulator is MODFLOW, and the optimizer is a simplex algorithm. These are included within the SOMO1 module of SOMOS. Necessary data includes: MODFLOW inputs concerning hydrogeology, wells, and historic water use; SOMOS inputs about candidate well locations, bounds on head, aquifer-stream seepage, and pumping

The 113 by 26 km (70 by 16 mile) Cache Valley area and aquifer is in northeastern Utah and southeastern Idaho (Figure 1). Most surface water, the primary irrigation source, originates in mountain snow. Groundwater results from precipitation, irrigation deep percolation, and seepage from surface waters. Wells provide domestic, industrial, public supply and irrigation water.
Groundwater pumping reduces surface water flow. Legal surface water rights and environmental protection should limit groundwater use. One compares ways of maximizing sustainable groundwater pumping by performing optimization for several groups of scenarios. Resulting optimal strategies are evaluated with respect to the heads and flows that would result from continuing 1990 pumping (termed the “background pumping rates”) to steady-state. Continuing 1990 pumping to steady-state is the ‘unmanaged scenario.’

Figure 2 shows the difference in flows between the unmanaged scenario and some Group A optimized scenarios. Group A scenarios maximize sustainable groundwater supply to 18 towns using one candidate new well site for each town subject to: (a) head at new pumping cells cannot decline more than 9 m (30 feet) in layers 1-4; (b) springs continue flowing where they flow in 1990 and in the unmanaged scenario; (c) saturated aquifer-river seepage continues where it occurs in 1990 and in the unmanaged scenario; and (d) total aquifer seepage to river cannot decrease by more than 10%.

Group A results show that sustainable pumping can increase 113-556 liters per second (4-20 cfs) above background rates. Other scenarios showed that even with more restrictive river depletion constraints, some sustainable groundwater pumping increase is possible. Such results encouraged the office of the state engineer to relax a moratorium on groundwater development.

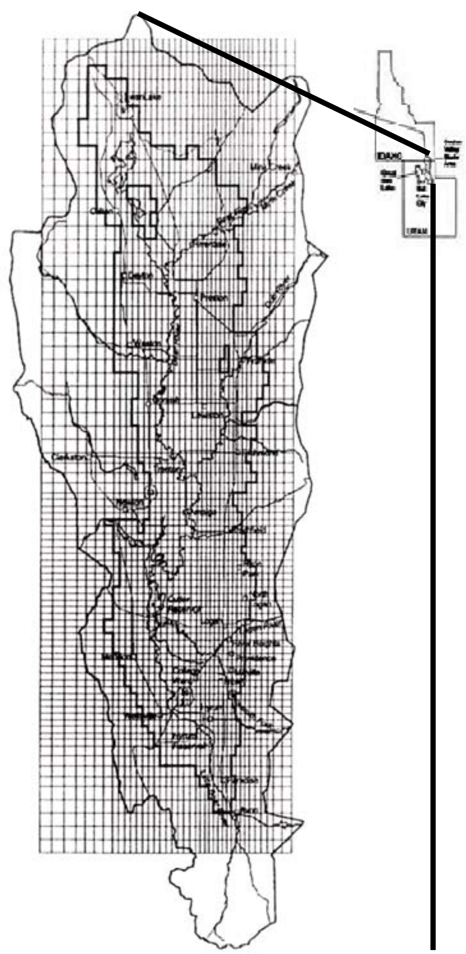

Figure1. Cache Valley location in Utah and Idaho, and groundwater model grid (from Kariya, et al., 1994).

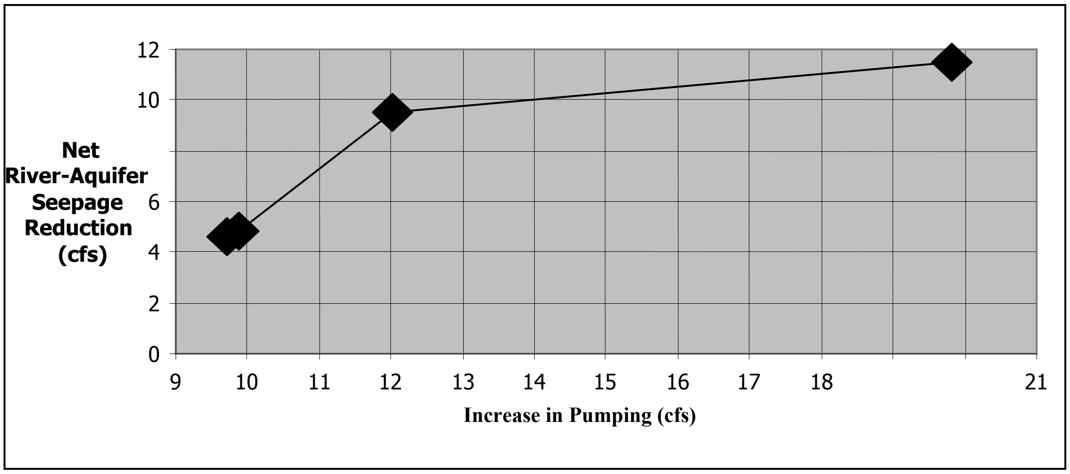

Figure 2. Tradeoff curve of groundwater pumping increase versus net river-aquifer seepage decrease (Peralta and Shulstad, 2004). (To convert cfs to m^3s^{-1} multiply by 0.0283.)

Remediation of Complex Aquifer Contamination

This study employed numerical groundwater flow and contaminant transport simulators, artificial neural network simulators, and heuristic optimizers (HOs), including genetic algorithm (GA), simulated annealing (SA), and tabu search (TS). Data includes that for the finite difference simulators, candidate well locations, concentration control zones, unit costs for the economic objective function, and bounds on head, pumping, and concentration.

The example is from work by Peralta et al (2002) optimizing PAT design for containing and removing a 7.5 mile (12 km) plume of trichloroethylene (TCE) and trinitrotoluene (TNT) at the Blaine Naval Ammunition Depot (NAD), in Hastings, Nebraska. Figure 3 shows the center of the 134 square mile (347 km^2) study area. The 66,912-cell model required 1.5 hours for one MODFLOW and MT3DMS simulation. They solved three optimization problem formulations requiring determining optimal pumping strategies for 12 to 25 wells and six five-year periods (60 stress periods) simultaneously.

Within three months, they developed optimal strategies for all three formulations using the SOMO3 module of SOMOS, (SSOL and HGS, 2001). Simultaneously, an experienced consultant team used the same MODFLOW and MT3DMS simulation models and the normal S model trial-and-error approach for designing strategies for the same problems. Both teams used a post-processor to compute the objective function value and evaluate results.

Figure 4 shows the Formulation 1 problem. SOMOS-developed strategies were 20-33 % better for all formulations than the trial-and-error-developed designs.

This is representative--for 8 sites at which our S/O-developed strategies were compared with trial-and-error designs, the S/O strategies were usually 20-40 % better (Peralta 2001b, 2003; Peralta et al, 2003).

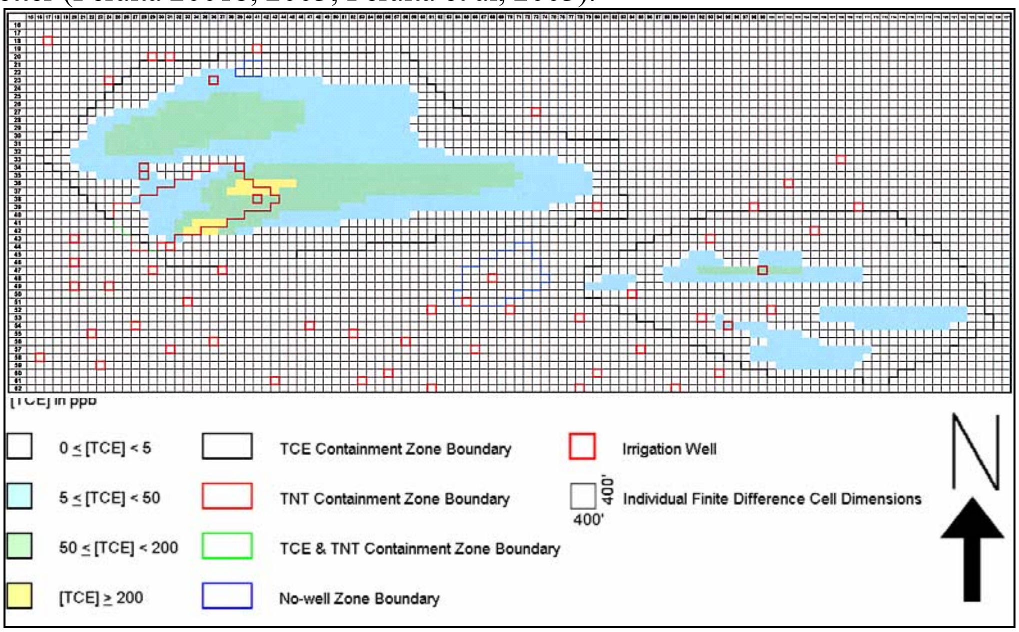

Figure 3. Initial (simulated 1 Jan 2003) TCE concentrations exceeding 5.0 ppb in layer 3, and part of finite difference grid (Peralta et al., 2003, 2004). (To convert from feet to meters multiply by 0.3048 m.)

Formulation 1 minimizes cleanup cost:

MINIMIZE Σ

{ Capital Costs of: wells (\$400K); treatment (\$1.0K gpm^{-1}); pipe (\$1.5K gpm^{-1}) }+ { Fixed Costs: management, O&M (\$115K yr^{-1}); sampling & analysis (\$300K yr^{-1}) }+{ Variable Costs: electricity (\$0.046K gpm^{-1}); treatment (\$0.283K per gpm^{-1}); discharge (\$0.066K gpm^{-1}) }

SUBJECT TO:

•Layer 1 and 2 cells not allowed to become dry

•350 gpm extraction limit per well per layer; no injection

•No remediation wells in layer 6, restricted areas or irrigation well cells

•Concentrations cannot exceed Concentration Limits (CLs) outside containment zones at end of any MP, (CL_{TCE} = 5ppb, CL_{TNT} = 2.8 ppb)

•Cleanup to CLs must be achieved within 30 years for Layers 3-6

Figure 4. Blaine NAD Formulation 1 optimization problem (Peralta et al., 2004). (Multiply gpm^{-1} by 264 to obtain m^3min^{-1}).

Optimizing Multi-objective Reservoir-Stream-Aquifer System Use

Fayad and Peralta (2004) report using multi-objective GA with ANNs for optimizing conjunctive use in a hydraulically connected reservoir-stream-aquifer system (Fig. 5). This approach reduces computer processing time yielding trade-off curves and surfaces for maximizing hydropower versus maximizing water delivery versus minimizing water delivery cost (Fig. 6).

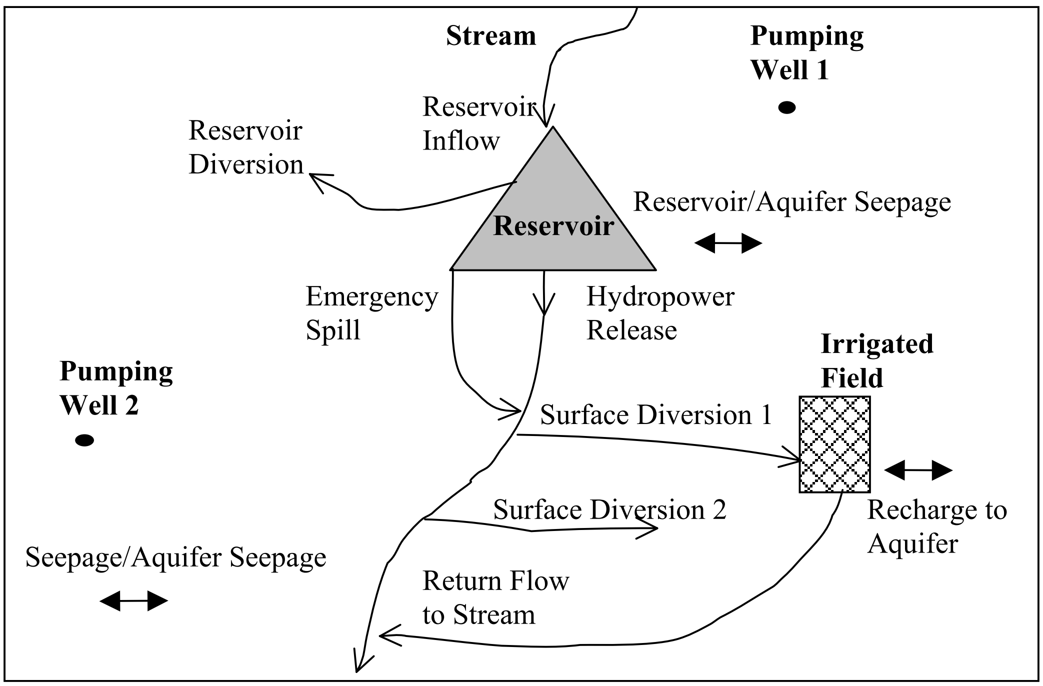

Figure 5. Study area conceptual view (Fayad and Peralta, 2004).

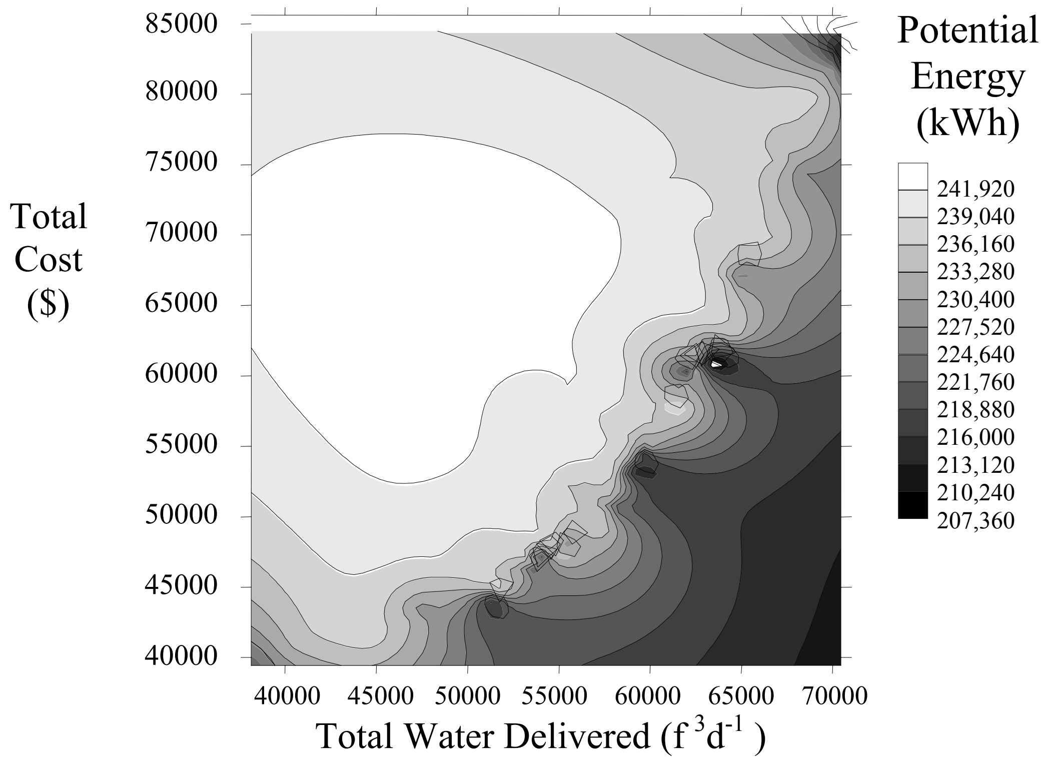

Figure 6. Tri-objective (water cost, water delivered, hydropower) trade-off surface (Fayad and Peralta, 2004).

SUMMARY

Simulation/Optimization models are becoming more flexible and powerful, leading to their increased use for aiding water policy-making, planning, systems design, and management. S/O models require data to: employ a suitably accurate simulator, and represent the objective function, constraints and bounds of the management problem. Thus, S/O models require more data than normal simulation models.

Different types of simulation and optimization approaches are better for different situations and management problems. For field settings where analytical flow equations are appropriate, an S/O module such as SOMOA can readily design optimal management strategies. SOMOA uses analytical and convolution (superposition) equations as simulators and classical operations research optimizers (simplex, branch and bound, and gradient search algorithms).

For heterogeneous aquifers describable via numerical flow models, optimization can also generally be performed using classical optimization algorithms. The

SOMOS SOMO1 module is appropriate for such aquifer and stream-aquifer systems.

For contaminated aquifers, where concentrations must be manageable state variables, it is usually best to employ numerical flow and transport simulators and heuristic optimizers. The SOMO3 module of SOMOS is applicable for most such sites. The SOMO4 generic optimizer can address systems for which more complicated simulation models are needed.

Designs or management strategies developed using S/O models are usually about 20-40 percent better than those developed using trial and error with simulation models alone. This is because simulation models are designed merely to predict system response to stimuli, but S/O models are designed to develop optimal solutions to user-specified problems.

SOMOS allows easy preparation of trade-off curves to evaluate the effect of constraints on objective function values, and to address multi-objective optimization problems. This is important because many water management problems are multi-objective. For example, trade-off curves can show how to use groundwater to achieve the best mix of sustainable population support and crop production, and ecosystem protection.

REFERENCES

Das, R. 2002. Planning sustainable optimal groundwater yield for the Utah part of Cache Valley. Irrigation Eng. MS thesis. Utah St. Univ., Logan, UT. 115 p.

Das, R., Peralta, R. C., and B. Timani. 2004. Cache Valley: optimizing sustainable water use and ecosystems while considering water rights. In Proceedings of EWRI 2004 World Congress.

Fayad, H. C., and R. C. Peralta. 2004. Multi-objective conjunctive use optimization. In Proceedings of EWRI 2004 World Congress.

Kariya, K.A., M.D. Roark and K.M. Hanson. 1994. "Hydrology of Cache Valley, Cache County, Utah and adjacent part of Idaho, with emphasis on simulation of ground-water flow," Tech.Pub., 108, Utah Dept. of Natural Rsrcs. 120p.

Peralta, R.C. 1999. Conjunctive Use of Ground Water and Surface Waters for Sustainable Agricultural Production. FAO of the United Nations Consultancy Report. 158p

Peralta, R. C. 2001. Remediation simulation/optimization demonstrations. In Proceedings of MODFLOW and Other Modeling Odysseys. 2001. Eds, Seo, Poeter, Zheng and Poeter, Pub. IGWMC. p. 651-657.

Peralta, R. C., Kalwij, I. M., and S. Wu. 2002. Optimal P&T designs for Blaine Naval Ammunition Depot. Proj. completion rep. for Navy. Systems Simul./Optim.Lab., Bio. & Irrig. Eng. Dept., Utah St. Univ. 36 p.

Peralta, R. C., *Kalwij, I. M. and B. *Timani. 2004. Optimizing complex plume pump and treat systems for Blaine Naval Ammunition Depot, Nebraska. In Proceedings of EWRI 2004 World Congress.

Peralta, R. C. 2003. SOMOS Simulation/Optimization Modeling System. In Proc., MODFLOW and More 2003: Understanding through Modeling, IGWMC, Golden, CO. p 819-823.

Peralta, R. C. and R. Shulstad. 2004. Optimization modeling for groundwater and conjunctive use water policy development. In Proceedings of FEM-MODFLOW Int.Conf., IAHS, Karlovy Vary, Czechoslovakia, Sep, 2004.

Peralta, R. C. and S. Wu. 2004. Software for Optimizing International Water Resources Management. In Proceedings of EWRI 2004 World Congress, ASCE, Salt Lake City, U.S.A. Jun, 2004.

Peralta, R. C., Kalwij, I. M. and S. Wu. 2003. Practical simulation /optimization modeling for groundwater quality and quantity man. In MODFLOW & More 2003: Understanding through Modeling, IGWMC, Golden, CO., p 784-788.

Systems Simulation/Optimization Lab. and HydroGeoSystems Group. 2001. Simulation/Optimization MOdeling System (SOMOS) users manual. SS/OL, Bio. & Irrig. Eng. Dept., Utah State Univ., Logan, Utah. 457 p.