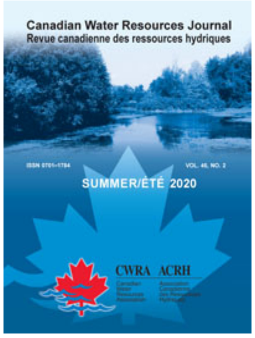

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New modeling paradigms for assessing future irrigation storage requirements: a case study of the Western irrigation district in Alberta

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ABSTRACT

River basin planning in Alberta has relied on the use of computer modeling since the early 1980s. Typical modeling studies rely on a single time step operational framework, where water allocation decisions are made for individual model time steps, without taking into account seasonal forecasts or the corresponding demand hedging rules that are often implemented by farming communities. This kind of modeling often leads to premature depletion of reservoir storage during dry years, producing model results that represent worse decisions than those that irrigators would make by using the rule-of-thumb. This paper critically reviews the current modeling practice, and provides insight into possible improvements in modeling through the use of multiple time step optimization in combination with optimal demand hedging, which is found as part of the model solution. A case study focuses on potential storage expansions in the Western Irrigation District of Southern Alberta. Improvements with the multiple time step optimization approach also shed new light on important water management decisions made in the past and the value of a revised definition of irrigation failure criteria. Finally, the selected modeling approach reveals significant potential for capital cost savings related to future infrastructure development, and suggests that investing in digital infrastructure – better forecasting and reservoir management tools – may be more productive than investment in additional physical infrastructure.

RÉSUMÉ

La gestion des bassins versants en Alberta repose sur l'utilisation de la modélisation informatique depuis le début des années 1980. Les études de modélisation classiques reposent sur un cadre opérationnel à pas de temps unique, dans lequel les décisions d'allocation de l'eau sont prises pour chaque pas de temps de modélisation individuellement, sans tenir compte des prévisions saisonnières ni des règles de restriction de la demande correspondantes souvent appliquées par les communautés agricoles. Ce type de modélisation conduit souvent à l'épuisement prématuré du stockage en eau dans les réservoirs pendant les années sèches, produisant ainsi des résultats de modélisation qui représentent de moins bonnes décisions que celles que prendraient les exploitants agricoles par experience. Cet article examine de manière critique la pratique actuelle en matière de modélisation des ressources en eau et donne un aperçu des améliorations possibles grâce à l'optimisation par pas de temps multiples, à l'aide d'une étude de cas d'expansion potentielle du stockage disponible dans le District d'Irrigation Western situé dans le sud de l'Alberta. Une meilleure gestion des reservoirs pour l'irrigation par la méthode d'optimisation par pas de temps multiples permet également de jeter un nouveau regard sur les décisions importantes prises dans le passé en matière de gestion des ressources en eau et sur l'utilité de redéfinir les critères d'échec de l'approvisionnement en eau pour l'irrigation.. Enfin, l'approche de modélisation choisie révèle un potentiel important d'économies de capital liées au développement futur d'infrastructures de stockage et suggère plutôt qu'investir dans l'infrastructure numérique - de meilleurs outils de prévision et de gestion des réservoirs - pourrait être plus productif que l'investissement dans une infrastructure physique supplémentaire.

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Gestion des réservoirs; approvisionnement en eau pour l'irrigation; optimisation par pas de temps multiples

Introduction

Water resources planning and development has relied heavily on the use of computer models in recent decades, to the point where computer modeling has become an integral part of modern water resources planning. River basin management models, which represent a unique class that aims to address water management and operations, are the focus of this paper. Such models can be useful for operating existing infrastructure or for identifying and selecting the

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best options for future infrastructure development. A distinguishing feature of all basin management models is their ability to mimic decision making, either by using a set of built-in “what-if” rules, or by relying on mathematical optimization algorithms to identify the best management or operational options from a wide range of possibilities. This mimicry is accomplished through minimizing or maximizing management objectives that are defined mathematically as objective functions. Several authors have provided summary papers that review the existing models, such as the review of reservoir operation models for basin planning purposes compiled by Wurbs (1993), which was subsequently updated by Labadie (2004). Each of those papers contains a short review of numerous existing models. Note, however, that there is no universally accepted river basin planning model, i.e. a model that would be used to provide benchmarks for all the others, although such models exist in other application domains – for example, the HEC-RAS model used in river engineering (Hydrologic Engineering Centre 2006). Most river basin management models that involve sophisticated optimization algorithms were not initially developed as university research projects, but were rather developed by government water management agencies and their respective ministries or by the private sector.

This paper compares current modeling practices, which rely on single time step model solutions in combination with reservoir rule curves specified as part of the model input data, with an alternative approach that optimizes model performance over multiple time steps (MTO). It also shows that MTO approach, in conjunction with an equal deficit sharing constraint, provides a way to simultaneously provide optimal hedging of water demands with optimization of storage releases. The pros and cons of the current solution approach are explained, and the alternative approach that optimizes over multiple time steps is presented. The study then compares the performance of the two approaches and reveals additional findings of potential interest to basin managers and stakeholders that highlight the importance of an audit of modeling results by stakeholders, in order to remove the impacts of possible errors and safeguard their interests in the best possible way.

River basin modeling – background and the current state of the art

The first optimization-based river basin management models for water distribution along water resources networks used simple linear programming algorithms specifically developed for the optimization of network flow problems, generally known as Network Flow Algorithms (NFA). One of the earliest examples is the SIMYLD model, developed by the Texas Water Development Board (Evanson and Mosley, 1970). Acres Inc. pioneered the development of a similar model in Canada and applied it in several previous studies in Ontario (Sigvaldason 1976).

A typical algorithm used for the early models was the Out-of-Kilter algorithm (Fulkerson 1961), which was subsequently improved most notably by Barr, Glover, and Klingman (1974) with their SUPERK algorithm, and Bertsekas and Tseng (1988) with the Relax4 network flow solver that is still used by the MODSIM (Labadie et al. 1986) and REALM models (REALM, 2006). While the NFA solvers offer high solution speed, they cannot easily represent dynamic constraints that exist in water resources networks. Their problem domain representation was limited to the mass balance at each node, and fixed upper and lower bounds on flow in each channel or river reach. To better represent actual constraints in water resources networks, it was necessary to address inherent non-network relationships that exist between various components, such as,

- Return flows from irrigation districts that depend on consumptive use, which can be described using a linear form with the consumptive use as an independent variable.
- Maximum reservoir outflows that are a function of average storage over a time step. Since the ending storage for a time step is not known and constitutes part of the model solution, the maximum outflow limit must be expressed as a function of storage. NFA algorithms cannot model the upper limit on flows in any component as dynamic variables that depend on flows in other components. A similar constraint may exist for the maximum diversion at a lateral weir, which may be a function of the upstream (incoming) flows.

The above constraints were initially addressed within NFA solvers using an iterative approach. However, iterations often fail to find optimal solutions, and in some instances actually take the solution process in the wrong direction (Ilich 2009). As river basin models grew in size and complexity over the years, repeated iterations often failed to converge to a feasible solution (Ilich 2008). This shortcoming led to the development of new models that use a commercial LP solver rather than the NFA solver. Such models include OASIS (Randall et al. 1997), RIVERWARE (Zagona et al. 2001), HEC-FCLP (Needham et al.

2000), VISTA (Hatch, 2019), and WRM-DSS (Water Resources Management Model, 2005), all of which use some form of Mixed Integer Programming (MIP) solver, since binary variables were required to ensure that reservoir zones fill from bottom to top, and empty from top to bottom (Ilich 2008). Models without binary variables, in cases where a reservoir was close to being empty for example, would incorrectly assign inflows to fill only the top storage zone, thus leaving one or more zones underneath empty. Consequently, most of the incoming flow could be allocated to downstream demands, since the top reservoir zone had the highest outflow capacity; however, this solution clearly represented a physical impossibility. The introduction of binary variables prevented this from happening, but with the shortcoming that model runs became significantly slower.

A river basin management model must be able to deal with the complexity of river basins. In addition to flexibility regarding network configuration, it should be able to model all major aspects of river basin management: large numbers of reservoirs, diversions for industrial, municipal and irrigation use, in-stream flow requirements, apportionment agreements between bordering states or provinces, hydro power production, evaporation, precipitation and local runoff. The heart of the model is the optimization sub-program that finds the best combination of reservoir releases and diversion flow rates for each simulated time step, subject to specified allocation priorities. In western North America, allocation priorities are determined by the age of each water license. Elsewhere, the allocation priorities can also represent monetary benefit per unit of flow for different types of water use. In general, LP solvers find optimal water allocations within a given river basin network by minimizing or maximizing the sum product of all flows and the given pricing vectors, i.e.

$$Max\sum_{i=1}^{n} Q_iP_i \leftrightarrow Min\sum_{i=1}^{n} ((I_i - Q_i)P_i$$

Where Q_i is the allocated flow, P_i is the pricing vector assigned to the users, I_i is the value of the upper bounds or ideal target, and i is the index of the user. The two formulations are equivalent, since maximizing flows is limited to the value of the ideal target I_i, where $I_i \geq Q_i$ for each user (represented as a model component associated with the flow variable) with an assigned priority. Maximizing flows to make them as close as possible to the ideal targets is therefore equivalent to minimizing deviations from the same targets, thus giving the same solution of allocated flows Q_i. The minimization form is typically known as a goal-oriented program.

Heuristic optimization algorithms and Multi-Objective optimization

This paper reviews algorithms that have been used successfully to build practical applications in river basin management, and outlines the difference between the current practice, based on reservoir rule curves, and the MTO approach proposed as its effective replacement. There is an important disconnect between academia and practice. First, with the notable exception of the MODSIM model (Labadie at al., 1986), virtually all other models commonly used by practitioners come either from a government agency (e.g. HEC by the US Corps of Engineers, WRMM or WRM-DSS by the Provincial Government of Alberta, or Water Evaluation and Planning Model (2019) developed by the Stockholm Environment Institute), or from the private sector (RiverWare, OASIS, MIKE-BASIN, and so on). Multi-objective optimization is an academic idea, with virtually no practical use among water management agencies – indeed, the most common models used in river basin management practice have no multi-objective optimization options. The same remarks are true for heuristic solvers, which have hardly had any use in solving large scale problems.

So why do models based on linear programming continue to dominate the practice? Firstly, because most problems in river basin management can be linearized effectively. Hydro power plants are the only non-linear component, and even they can be successfully linearized, as shown by Kang, Chen, and Wang (2018). In spite of the strength of LP approaches, significant academic effort has been devoted to investigate various new solution approaches, known generally as heuristic algorithms, which are typically based on the concept of evolutionary progression towards better solutions that mimics biological processes. Linear programming can successfully solve problems with hundreds of thousands of variables – Lund (2003) solved optimization problems with 5 million variables using HEC-ResPRM (Hydrologic Engineering Centre, 2006). On the other hand, most heuristic solvers in the water resources sector solve small test problems with very little practical use. For example, the Honey Bee mating algorithm (Bozorg-Haddad, Afshar, and Mariño 2011, Bozorg-Haddad et al. 2017) was recently tested on a system with 4 reservoirs and 12 consecutive time steps, i.e. a total of 48 variables, and a similar larger system with 10

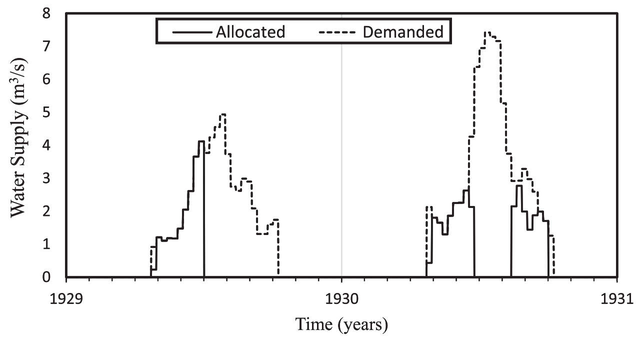

Figure 1. Single time step solutions (dashed line – water demands, solid line – achieved supply).

reservoirs for over 4 consecutive years with monthly time steps, for a total of 480 variables. These two test problems are very old (Murray and Yakowitz 1979), simple and linear, without net evaporation on reservoirs or dynamic flow limits imposed by the available storage.

LP solutions can be developed for these problems within a few hours that solves within a fraction of a second. Moravej and Hosseini-Moghari (2016) have also solved these test problems using their Interior Search algorithm, and the title of their paper "Large Scale Reservoir System Optimization" is symptomatic of their disconnect with practice. Etheram et al. (2017) and Allawi et al. (2018) used the so-called Shark algorithm to claim that they have found optimal solutions faster than the other heuristic methods. Most other researchers acknowledged that their solutions were inferior to the LP solution, even for a small problem of this size. Practitioners in the water resources sector require reliable and fast solvers for hundreds of thousands of variables. Heuristic solvers are still far from achieving this.

Two recent papers provide more in-depth coverage of the use of optimization in water resources. Dobson et al. (2019) review the use of optimization, distinguish between rule curve-based models and multiple time step solutions, and outline the need to apply artificial intelligence algorithms that can learn from numerous MTO solutions and apply their results in real time operation. As a review of on-going research efforts in academia, this paper also provides an in-depth survey of the available literature on heuristic solvers. Further, Dobson et al. (2019) provide a simple test problem with one reservoir and two withdrawals, to be solved over multiple time steps. Their objective function minimizes the sum of the squares of differences between the supplied and demanded water quantities, thus creating an artificially non-linear problem. This formulation is not necessary, since the supplied amount would never be greater than demanded. In the Matlab text files they provide in the link in the paper, the authors state that they also derived an LP solution to this problem by using a simple constraint that the supplied amount should be less or equal to the demanded. This amounts to a lot of intellectual effort to solve problems heuristically that can be more effectively and easily be solved by using a spreadsheet solver or Matlab. Gavahi et. al (2019) offers an interesting example of a single reservoir optimization problem solved with MTO, where the MTO solutions are fed as input into an adaptive neuro-fuzzy system along with one month inflow forecast based on the regression of the flows in the three previous months. Their intent was to achieve monthly releases in real time that are similar to the MTO solutions for similar inflow conditions and starting reservoir levels, without using any user defined rule curve. While monthly time step solutions may not be the best choice for real time operation, it should be noted that the MTO solutions in this paper were obtained using linear programming.

In summary, a) problems in river basin modeling can be linearized in large majority of the cases, which makes linear programming the most suitable solution procedure due their speed and guaranteed accuracy of the solution; b) all well-known models used by practitioners rely on linear programming; c) academic efforts to investigate various heuristic solvers have been limited to small and simplified test problems; and d) for all of the above reasons, the heuristic algorithms have not been incorporated into any well-known water resources models that are commonly accepted among practitioners.

The concept of reservoir rule curves

The principal disadvantage of using the above objective function as a guideline for water allocation is the fact that its solution addresses single time steps independently, an approach usually called Single Timestep Optimization (STO). It can still provide helpful insights when resolving water allocation with many users in a system with multiple reservoirs, but it may result in reservoirs emptying prematurely during an irrigation season, which compromises the water supply for the remainder of the season. Typical results for very dry years are shown in Figure 1 below.

The modeled irrigation supply shown in Figure 1 results in crop failure in both years. To avoid it, irrigation managers typically hedge their demands in extremely dry years – in other words, they lower their targets to reduce the chances of crop failure. Their dilemma is then to determine the level of reduction that

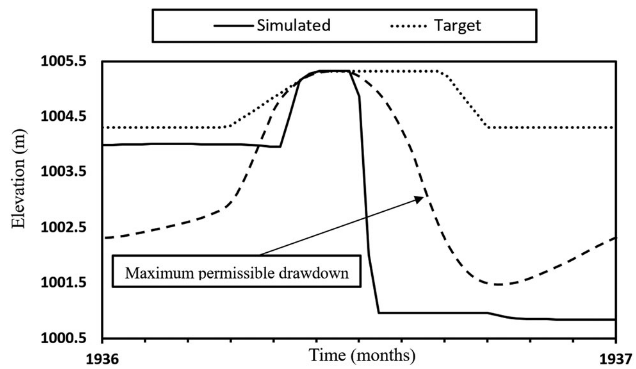

Figure 2. Concept of reservoir rule curve.

is most appropriate for the current conditions. One of the ways that modeling can be useful is to provide them with the appropriate level of reduction, and that level is part of the LP solution obtained through simultaneous optimization of supply and demand.

Ravelle (1970) developed the concept of the reservoir rule curve in an effort to avoid the STO solutions shown in Figure 1. A rule curve allows model users to input a maximum permissible drawdown curve, with a high penalty factor associated with modeled water levels that fall below this curve. In essence, the curve defines the amount of available conservation storage. Figure 2 shows this storage as the volume between the dotted line (the maximum storage) and the dashed line (the minimum storage). If reservoir drawdown below the dashed line were not allowed, the premature emptying of reservoir storage (shown as the "simulated" value) would be prevented, and a guaranteed minimum water supply would be available for irrigation throughout the irrigation season.

Most river basin planning models rely on reservoir operating rules, as defined by the shape of their rule curves. The inherent problem with rule curves is the dependence of their shape on both the storage at the beginning of an irrigation season and the combination of available runoff and water demands throughout the season. To illustrate the problem, imagine there are two back-to-back dry years such that the model cannot reach the full supply level and subsequently cannot follow the prescribed rule curve, which typically assumes a starting position at the full supply level. In a strict sense, a pre-defined rule curve represents an attempt to guess the best storage levels that will minimize all water supply deficits for several months in advance. However, the magnitude of water deficits and their distribution should be solved by the model, rather than assumed by the user. If a reservoir rule curve is defined as the set of ideal elevations at the end of each time step that best meets all reservoir operational objectives, its best shape can only be seen in the MTO solution. Further, the shape of the rule curve should obviously be unique for each simulated year, since each year will have different starting storage levels and different hydrologic inputs.

Just as the ideal rule curve shape is different for every year, it is also related to the amount of hedging of water demands, if and when hedging is required. Therefore, the amount of hedging and the shape of the rule curve are set simultaneously. Importantly, MTO should be used to determine both the best rule curve shape and the best hedging levels with starting storage levels and seasonal runoff forecasts as the only inputs – this is the principal idea put forward in this work.

Reservoir rule curves should not be developed on the basis of operator experience, since operators often make significant errors of judgment that should not serve as golden rules for future management. The main advantage of the MTO modeling approach presented below is that rule curves are not required as model input. Rather, they are provided as part of the model solution, and are unique for every year. Thus, the main purpose of this paper is to demonstrate that MTO modeling removes the need for any rule curves, since MTO, in combination with equal deficit sharing constraints, simultaneously provides the optimal rule curve and the optimal level of water use in each simulated year. With the acceptance of the proposed MTO approach, future research should focus on better seasonal hydrologic runoff forecasts.

Multiple time step optimization

Multiple Time Step Optimization (MTO) offers significant improvement in the model results, especially when combined with equal deficit sharing constraints, which is a novel approach for optimized demand hedging presented in this paper. Numerous recent studies and publications have examined its advantages, and it was the basis of the California State Water plan (Lund et al., 2003).

An MTO model can find the best operating policy for each reservoir in each year, while simultaneously ensuring that all irrigation blocks supported by the same reservoirs have equal deficits throughout the irrigation season. To achieve this, the model should:

(a) Optimize over multiple time steps;
(b) Use equal deficit sharing constraint within each irrigation season; and,
(c) Avoid applying any user defined rule curves, since the model will derive them as part of the optimal solution.

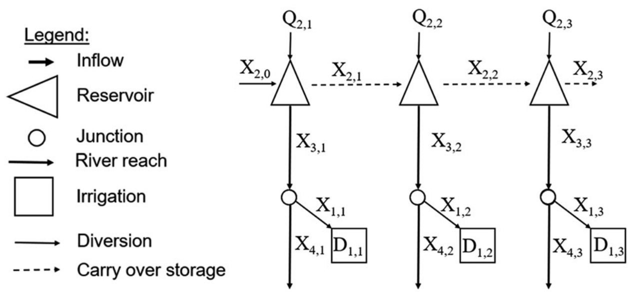

Figure 3. Sample model configuration for solving three time steps simultaneously.

When set up in the above manner, the model provides insight into the optimal operation for every hydrologic year on the record. The model solutions then constitute perfect rule curves derived uniquely for each hydrologic year. To explain the approach, a simultaneous water allocation optimization over three time steps is illustrated on a simple model schematic in Figure 3 below, which includes one reservoir, two river reaches, one diversion canal and one irrigation block. The same approach can be used to solve the entire hydrologic year for much larger systems. Decision variables are channel flows and storage volumes at the end of each time step, designated as variables $X_{i,t}$ in Figure 3, with subscripts for component i and time interval t. Variables are assumed to be in units of flow as explained below, so that $X_{2,0} = \frac{V_o}{t}$ represents the reservoir storage at the start of the simulation, t = 0. If the model were set up to run single time step solutions, only the left third of Figure 3 would be shown, consisting of the reservoir in the first week with inflow, outflow channel, initial and ending storage volumes, and diversion $X_{1,1}$ into an irrigation block with its demand of $D_{1,1}$.

If the reservoir storages and available inflow provide sufficient water, then $X_{1,1} = D_{1,1}$ (i.e. supply equals demand) and there are no deficits.

The initial storage at the beginning of the first time interval $X_{2,0}$ is given, while variables $X_{2,t}$ represent ending storage (in units of flow) at the end of each subsequent time interval t, which automatically becomes the starting storage at the beginning of the next time interval. Net evaporation is omitted in this example, but is modeled in principle as a gain or loss of flow along the reservoir carry-over storage arc.

To define an objective function for the model in Figure 3, assume a weekly time interval, a value of storage of \$1 per one unit of storage, and a unit of storage corresponding to 1 m^3/s of flow over the length of the weekly time step. When converted to storage, this equals $86400 \times 7 = 604.8$ dam^3. Storage requires a value, so that the model avoids spilling water from the reservoir unnecessarily. It can also be assumed that supply to irrigation blocks defined by variables $X_{1,1}$, $X_{1,2}$ and $X_{1,3}$ has a benefit function of \$100 per 1 m^3/s of supplied flow. Again, for simplicity, all other cost factors associated with flows in the two river reaches (one before and one after the diversion into the irrigation block) can be set to zero in this example. The objective function is then specified as:

$$Max \sum_{i=1}^{n} \sum_{t=1}^{m} X_{i,t} P_i$$

Where $n = 4$ is the number of components, since it involves one reservoir, one irrigation block and two river reaches, and $m = 3$ is the total number of time intervals in Figure 3, although their number is usually set to 52 to cover all weeks within a year. Note that carry over storage also acts as a variable, since it allows the model to balance storage among various time intervals.

The above objective function is subject to the following constraints:

$$X_{2,t} + X_{3,t} - X_{2,t-1} = Q_{2,t} \text{(balance equations for reservoir, } t = 1, m)$$

$$X_{1,t} - X_{3,t} + X_{4,t} = 0 \text{ (balance equation for irrigation diversion node, } t = 1, m)$$

$$0 \le X_{i,t} \le U_{i,t} \text{ (definition of lower and upper bounds on all variables, } i = 1, n;\ t = 1, m)$$

Upper bounds represent limits on storage, canal capacity, or irrigation demand. For example, irrigation supply $X_{1,t}$ will never exceed the specified demand $D_{1,t}$ for a particular time interval. The flow in the natural channel theoretically has no upper limit, but it can be set to a much larger number than the probable maximum flood to satisfy the requirement for upper bounds on the variables imposed by most commercial LP solvers. The number of time steps solved simultaneously usually equals the number of time steps modeled in a single year (i.e. $m = 52$ for weekly simulation).

The linear program definition above does not clearly define how the model should handle water supply deficits. The objective function produces a cost of \$100 for a 1 m^3/s deficit, but the model is indifferent as to how the irrigation deficits are distributed, since the cost of deficits per unit of flow is the same in all time intervals t. Therefore, if the starting storage is low and the inflows are insufficient to meet irrigation block demands, the model may allocate all deficits to certain

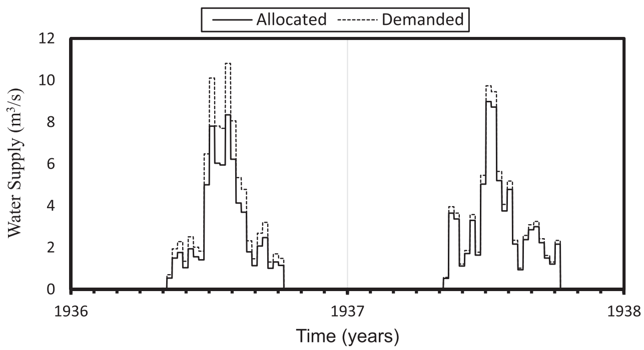

Figure 4. Equal deficit distributions (broken line is ideal demand, solid line is achieved supply).

time steps, and full supply to other time steps, thus creating a solution that resembles the irrigation supply shown in Figure 1. In such a case, the MTO solution is not better than the STO solution! One possible solution to this would be to discretize the irrigation demand into a number of zones, where for example each zone could cover an incremental increase of 10% of the total demand, and assign increasing cost factors to each zone in the direction of increased deficits. However, this would create 10 times as many more irrigation variables in the problem (since each zone is treated by the solver as a separate variable), and would still allow variation of the supply deficit of up to 10% from one time interval to another. To avoid this problem, an equal deficit constraint is added that takes the following mathematical form:

$$\frac{X_{1,t+1}}{D_{1,t+1}} = \frac{X_{1,t}}{D_{1,t}}$$

The above constraint forces the ratio of the supplied amount X_t to the required amount D_t in time interval t to be the same as the ratio of the supplied amount X_{t+1} to the demand D_{t+1} in the next time interval $t+1$. Therefore, if deficits are inevitable, the model will spread them evenly over the entire irrigation season. This constraint ensures that the solver will minimize deficits by balancing storage and inflows conjunctively in all time steps, as well as spread the deficits evenly through all time steps, without using any additional variables. In other words, the constraint manages the spread and the magnitude of deficits in the best possible way, and allows the solver to find the best way to hedge water demands as part of an LP solution.

The outcome of this approach is twofold:

(a) By spreading the irrigation deficits evenly over the entire season, the model *de facto* determines the size of irrigated area that can be serviced without deficits in each hydrologic year, while accounting for all other stakeholders' demands and priorities. In other words, solutions that make no sense, such as those shown in Figure 1, are eliminated, without the need to guess the shape of a rule curve.

(b) The model finds the best operating rule for each year and for all reservoirs simultaneously – in other words, it derives the ideal rule curve for each hydrologic year. This allows the user to statistically analyze the obtained rule curve shapes for all simulated years and obtain additional information about the anticipated range of reservoir levels throughout the year for various hydrologic years and starting storage levels.

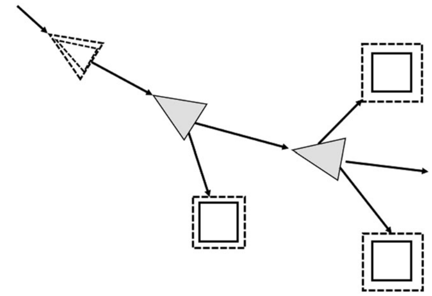

Figure 5. Possible water use and storage expansion scenarios.

An example of a model solution for years with deficits is shown in Figure 4.

The upper histogram in Figure 4 shows the ideal demand, while the lower one shows the achieved supply. Deviations in the shapes from typical crop demand curves result from the effects of precipitation, which was included in assessing seasonal irrigation demands. Solutions in Figure 4 can best be interpreted as the maximum area of irrigated land in each hydrologic year that could be cultivated without deficits. The above modeling approach gives users the ability to modify the sizes of both irrigated areas (representing future expansion alternatives) and additional storage facilities, as shown in Figure 5. Each modeling scenario can then examine the impact of additional water use and/or storage. Further, the costs of additional infrastructure can be matched against the benefits of meeting future water use objectives, providing valuable input for economic analyses.

Therefore, the benefits the MTO approach can be summarized as follows:

(a) MTO finds the best possible reservoir operation for each simulated year;

(b) It provides simultaneous optimization of supply and demand; and,

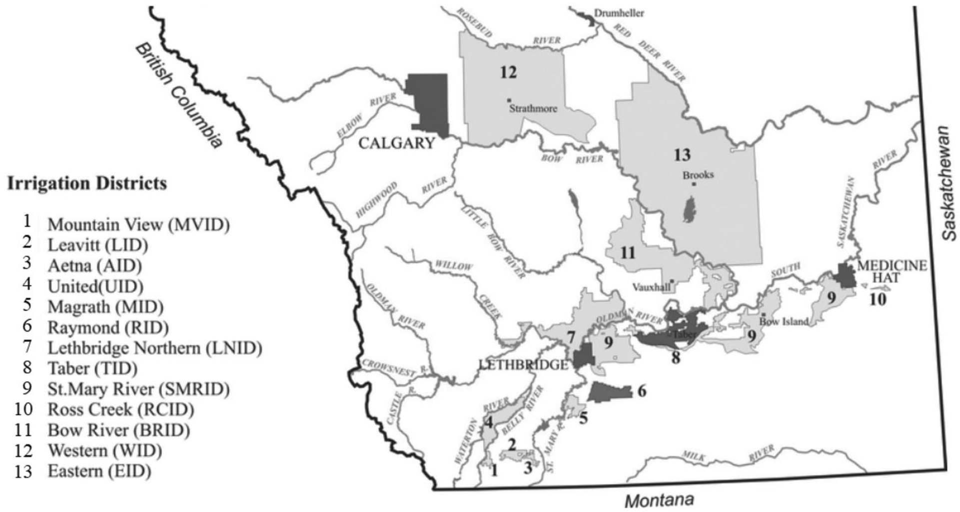

Figure 6. Irrigation districts in Alberta. Source: Prof. Kurt Klein

(c) It does not require assumptions about reservoir rule curves (because they are part of the model's solution).

The greater quality of MTO-based solutions, as compared with the previous solutions based on reservoir rule curve use, has inspired decision makers to look for ways to implement the MTO approach in seasonal operation, based on seasonal forecasts of runoff and water requirements and on known storage levels at the beginning of the forecasted time horizon. Irrigation districts, with their internal storage reservoirs and water supply provided through diversion canals, provide an excellent case study for MTO application, since the uncertainty of runoff predictions is minimized by the fact that runoff originating within the District is not a critical factor in the overall water supply. The following numerical example demonstrates the benefit of applying the MTO approach to the Western Irrigation District in Southern Alberta, Canada.

Numerical example

The Western Irrigation District (www.wid.net) is one of the 13 irrigation districts located in Southern Alberta, Canada, with a license to irrigate 38,445 hectares. In total, the 13 districts comprise 587,000 hectares of irrigated land. As of 2016, this constitutes more than 70% of the total irrigated land in Canada. A map of Southern Alberta with the districts is shown in Figure 6, with the WID labeled as number 12.

The Western Irrigation District receives its water supply through the WID headworks canal that diverts water from the Bow River in Calgary into Chestermere Lake, and from there to a network of canals, as shown in the modeling schematic of the Western Irrigation District (WID) in Figure 7. The supply is limited by the canal capacity and the limitations imposed on the water license by Alberta Environment and Parks (AEP), a Provincial Government regulatory agency in charge of issuing water licenses and managing water resources in the Province. This study used input data from AEP and Alberta Agriculture and Forestry (AAF), also a Provincial Government agency. The modeling schematic shown in Figure 7 was inherited from AEP. Note the addition of the proposed Bruce Lake reservoir, evaluated initially for a planned storage volume of 45,500 dam^3.

Water resources management in Alberta relies to a large extent on studies that apply computer models in an STO-based approach. However, a comparison between the currently used STO simulation with the MTO simulation conducted as part of this study reveals significant differences, as depicted in Figures 8 and 9. Figure 8 shows the total annual deficits in supply calculated as the relative difference between the total annual water demand and the total volume supplied to the district expressed as a fraction of the annual demand. There are only five years with annual deficits that range between 5% and 8% of the demand in the MTO mode with an overall average of 0.4%, while the standard STO approach yields deficits every year, ranging from 0.3 to 11.3% with an overall average of 3.6%.

Application of the irrigation failure criteria used in the past (the threshold is defined as the annual deficit of more than 10% on an annual basis, with the frequency of occurrence of no more than once in ten

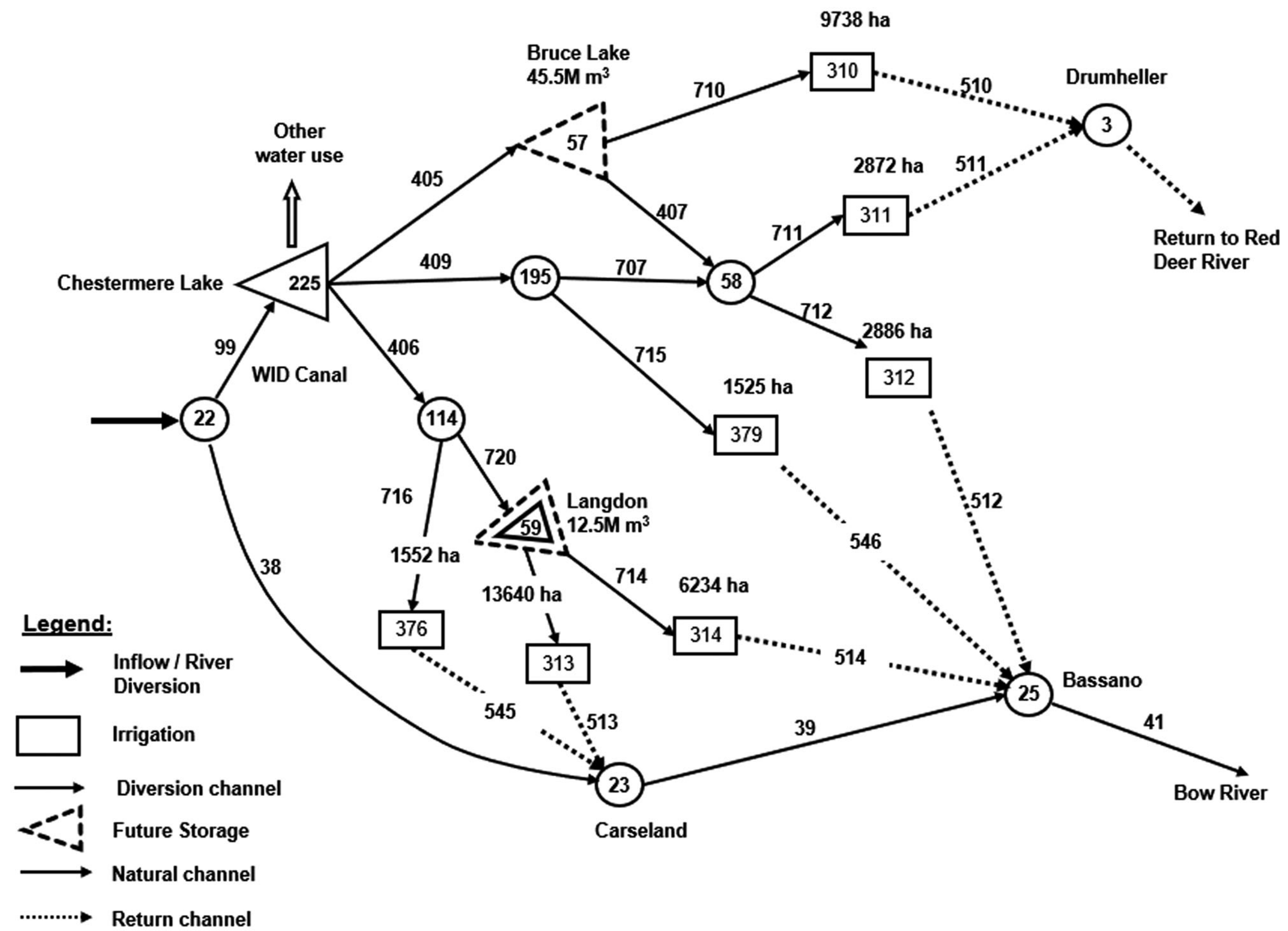

Figure 7. Modeling schematic of the Western Irrigation district.

years on average) to the MTO results suggests that the proposed Bruce Lake reservoir is oversized.

Hence, three additional simulations were tested iteratively, assuming various smaller storage levels for Bruce Lake. These simulations included 50% of the proposed storage, 30% of the proposed storage, and a fourth simulation based on the previous three of 35% of the proposed storage. They revealed that 35% of the proposed Bruce Lake storage size is sufficient to pass the existing irrigation failure criteria, with 7 of 74 individual years (i.e. fewer than 10% of the total) having deficits higher than 10%. Each simulation was followed by appropriate statistical analyses of the output. Annual deficits with reduced storage on Bruce Lake are shown in Figure 9.

Another important modeling topic is the sharing of irrigation deficits in time and space between various irrigation blocks. In STO simulations, one component often suffers higher deficits than another, even though they should have the same priority of allocation. For example, the STO solution setup inherited for this study shows higher deficits on block 314 (one of the two blocks supplied by the storage in Langdon reservoir) compared to other blocks. These deficits are shown in Figure 10, which is based on the full proposed storage at Bruce Lake. Importantly, while some irrigation blocks had no deficits in any years, block 314 suffered deficits in all years with a wider range that exceeded 50% of water demand in two simulated years and more than 30% in six additional simulated years, in spite of the storage from Langdon reservoir as its designated source of supply. Its connection to Langdon suggests that this irrigation block should not have the worst performance in the system, since there are blocks without any direct internal storage support (note that Chestermere Lake does not count as a source of water for irrigation; its water levels are primarily maintained for recreational purposes). The deficit in block 314 can result from a combination of factors, including the use of STO solution strategy along with an improper setup of priorities in the input data file. In contrast, deficits were below 10% for block 314 in only 5 of 74 simulated years using the MTO solution approach, as depicted with dark bars in Figure 10.

Uneven deficit spreads are common throughout an irrigation season in STO results, as shown in Figure 11,

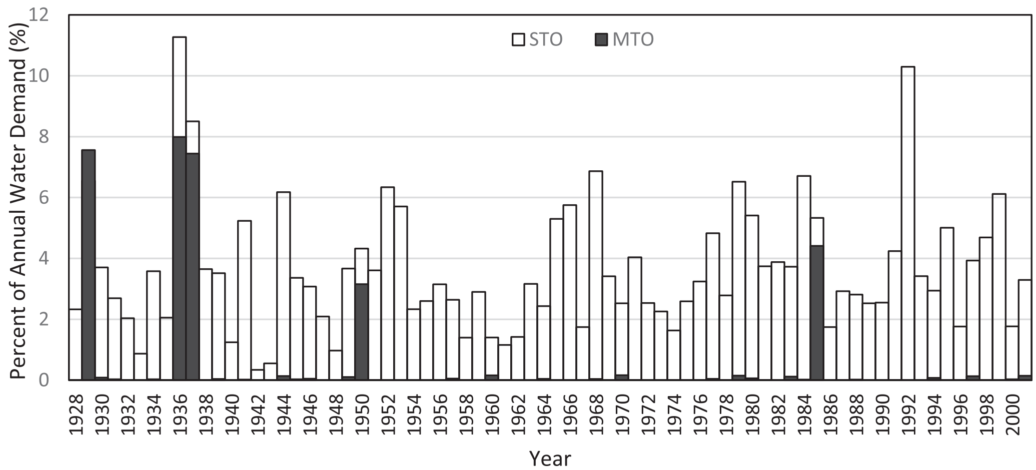

Figure 8. Annual deficits for WID with proposed storage expansion (%).

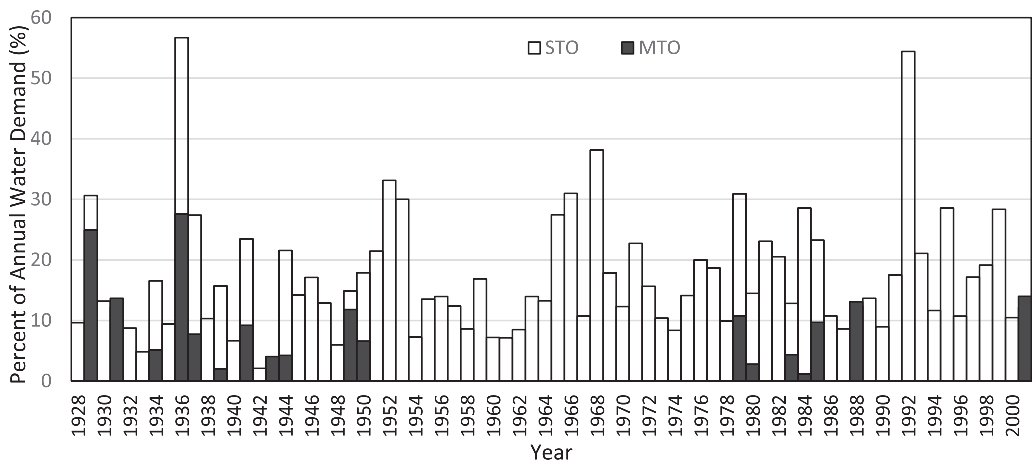

Figure 9. Annual deficits for WID with 35% of the proposed storage expansion.

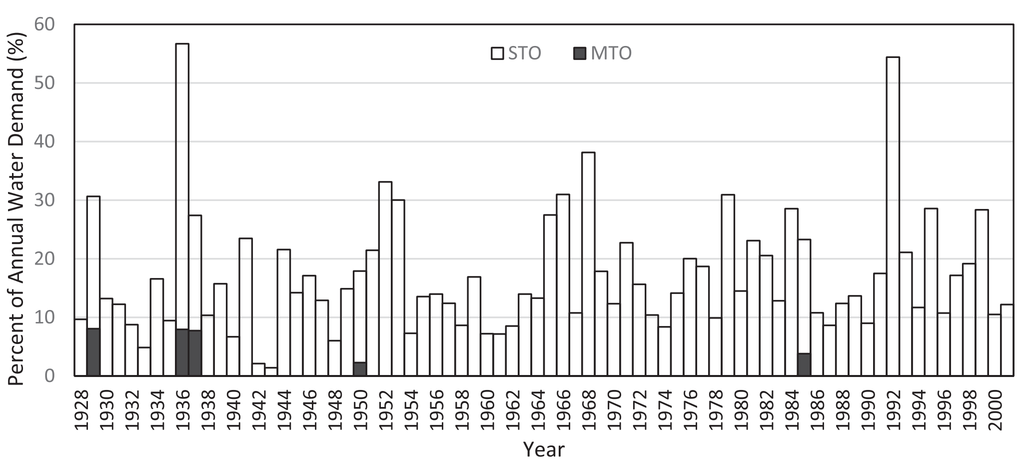

Figure 10. Annual deficits of block 314 with the proposed storage expansion.

which clearly indicates likely crop failures in 1936 and 1937. These results should be compared with results shown in Figure 12 based on equal deficit sharing in time and among all five blocks supplied by Langdon and Bruce Lake reservoirs (i.e. all but blocks 376 and 379 in Figure 7).

The greater allocation to block 314 in MTO simulation compared to STO results from the smaller allocation to block 376, which receives more supply in STO simulation because of a slightly higher priority given to blocks that are not supported by storage (2.6% annual deficits compared to 34% in MTO simulation). In STO

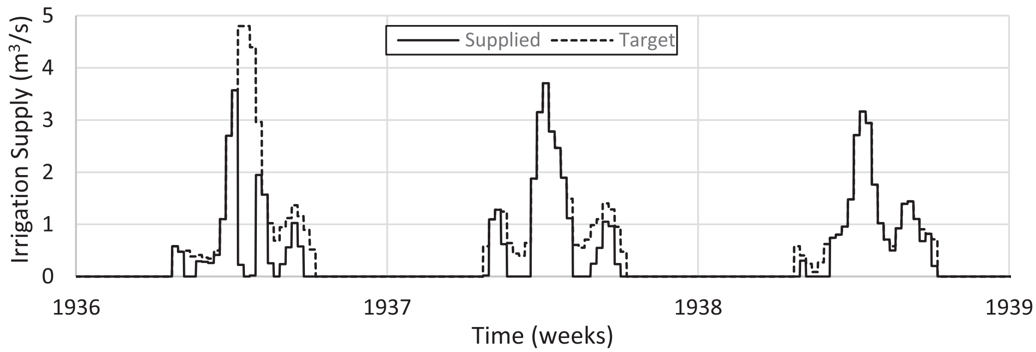

Figure 11. Water allocations to block 314, STO Solution.

simulation, storage at Langdon reservoir is therefore depleted faster than in MTO simulation, since the flows are directed to block 376 first and only the surplus is stored in Langdon and distributed to blocks 313 and 314. However, with MTO, the storage is balanced between all three blocks, which prevents crop failure in block 314. Further, the total volume of deficits for all irrigation blocks in 1936 is 4124 dam^3 in STO run and 3264 dam^3 for MTO run, which is only marginally better. However, comparison of seasonal total deficits between MTO and STO runs ignores the fact that the MTO run ensures no crop failures, while STO may allow no supply for weeks at a time (Figure 11). With the STO run, a crop failure in any block should be counted as 100% deficit for the entire year for that block, regardless of the amount of water allocated to the block prior to crop failure.

Figures 11 and 12 demonstrate the need to revisit the methodology for evaluating deficits. For example, the failure criteria set to the threshold of annual deficits at 10% or more should be revised to include analyses of their temporal distribution in addition to the magnitude. Many water management agencies analyze deficits from model runs without distinguishing crop failure from deficits that are equally spread over all time intervals.

Simulated storage levels are also more stable in MTO solution. Of the two reservoirs, Bruce Lake has four times larger storage, so it would be insightful to compare its storage levels in STO and MTO simulations during the critical dry months. This comparison is provided in Figure 13, which shows more stored water in dry years in MTO run than in STO run. In particular, for 1:5 and 1:10 dry years, there is 1.5 m more storage in Bruce Lake. This provides additional insurance in dry years.

Definition of maximum withdrawals into WID canal

Various ways exist to determine maximum water diversions in each simulated year into the WID headworks canal, which supplies the entire Western Irrigation District. The data initially supplied by AEP employed an iterative technique that ran the entire WID District independently from the full South Saskatchewan basin by using a fictitious storage at the top of the WID headworks canal as its water supply. These constituted the target flows in the WID headworks canal, and were then input as a separate demand in the larger model of the entire South Saskatchewan River Basin (SSRB), where the WID license was then combined with other senior water licenses such as the ones held by the Eastern Irrigation District (EID) and the Bow River Irrigation District (BRID), and other in-stream flow requirements imposed by AEP that are typically modeled as fish rule curves.

The entire SSRB model was run in the STO mode, and this project did not change the overall approach. However, a large discrepancy between the WID license and the average diverted volume called for an examination of the approach. Specifically, the entire WID license is 343 million m^3, while the average diverted volume using the modeling approach described above was 161 million m^3. In order to determine maximum possible diversions from the Bow River that did not violate any other senior constraints, in-stream flow conditions and the apportionment agreement, two small changes were introduced in the assumptions:

(1) The internal storage reservoirs start each year empty, and they need to be refilled during the season while irrigation supplies are provided simultaneously; and,
(2) For the remainder of the season, the internal storage reservoirs should be kept full as "backup" or "insurance" that additional source of supply will be available in case there is no sufficient supply from the Bow River.

These two assumptions introduce the upper limit on the diversions that can possibly be demanded

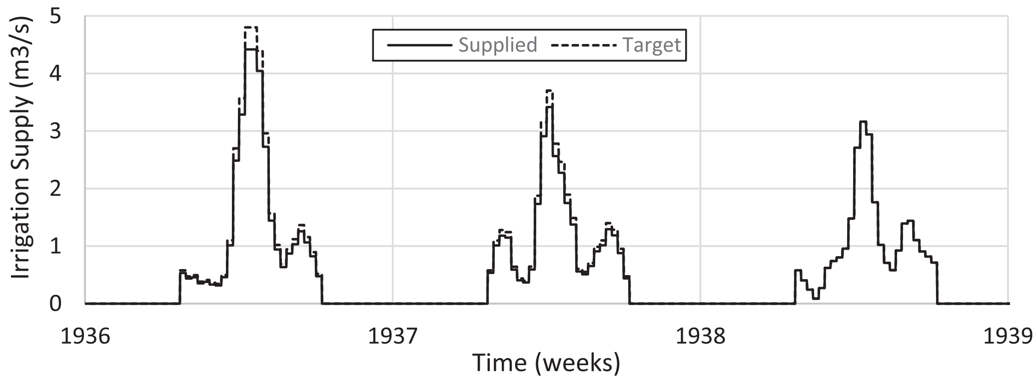

Figure 12. Water allocations to block 314, MTO Solution.

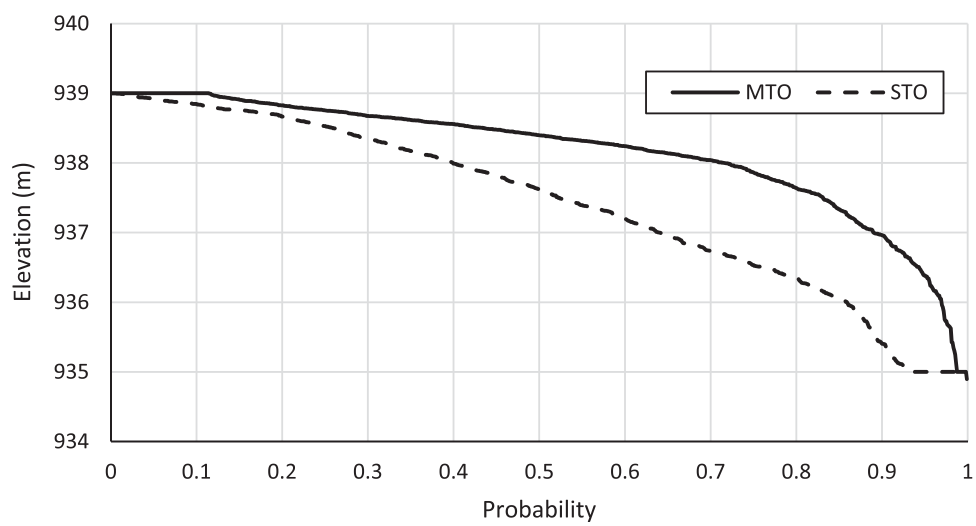

Figure 13. Bruce lake summer water levels (Jul. 1 - Aug. 31).

from the Bow River at the headworks of the WID canal. The actual supply to the district determined by the SSRB simulation will often be less than this demand, due to the apportionment agreement and other senior water licenses in the Bow River Basin. In other words, running the SSRB model in this fashion shows how much of this maximum demand could be met from the Bow River in each simulated year. To produce the ideal supply run required the following steps:

(a) Redefine the upper limit of WID water demands as higher than the current limit, but still within the limits of the water license;
(b) Re-run the entire SSRB scenario using the new ideal targets obtained in step a);
(c) Analyze the results from the entire SSRB in step b) to establish whether more water can be diverted into the Western Irrigation District without negative effects for any other stakeholders in the SSRB with senior water licenses, in-stream flow objectives as well as the apportionment.

Figure 14 shows the results of this exercise. In particular, note that the average water supply into the WID could have been increased from 161 million m^3 to 192.5 million m^3 without negative impacts on other stakeholders, environmental flows or the apportionment targets at the Provincial border between Alberta and Saskatchewan.

The above strategy explained by the steps a), b) and c) emerged from an examination of the temporal distribution of flows within the districts in all previous simulation runs based on the diversions estimated by AEP, and revealed that it is possible to withdraw more water from the Bow River compared to earlier analyses conducted by AEP. The district water allocation was found to rely heavily on internal storage releases in the second half of the irrigation season, to the extent that almost zero diversion occurred from the Bow in the last 10 – 12 weeks of the irrigation season, causing the internal storage reservoirs to always end the year empty. Yet, this approach may be problematic if subsequent years are dry. Instead, internal storage reservoirs do not have to be empty at the end

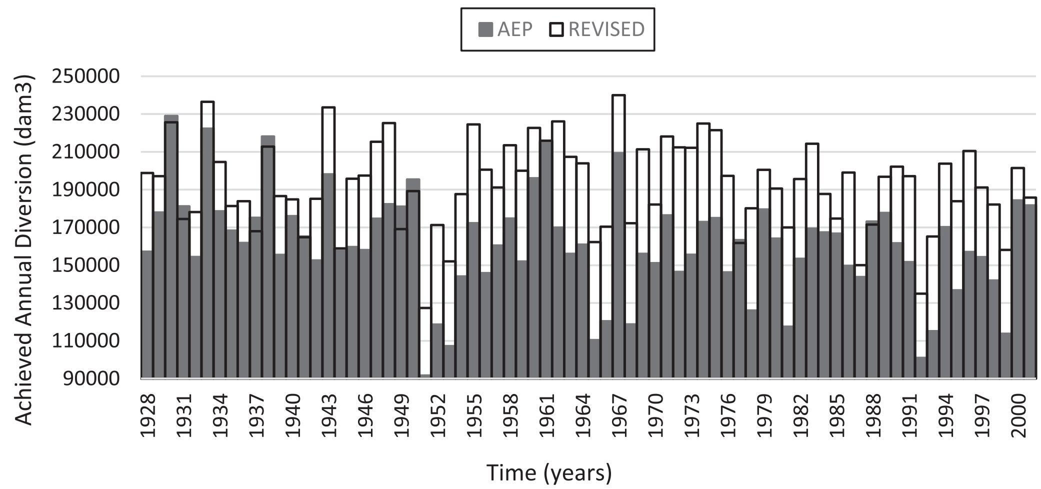

Figure 14. Annual diversions from SSRB into the WID headworks canal.

of each irrigation season. Having some left-over storage from the previous year is especially useful in dry years with insufficient water supply.

Future developments

The MTO solution approach can be applied for seasonal water management in near real time especially at the end of the high flow season, using statistical seasonal flow forecasts generated with inferential models that rely on local temperature, precipitation, streamflow and snow pack survey data, and large-scale climate indices. Moreover, irrigation districts have water licenses that are related to regulated flows, which in the Bow River Basin are affected by Transalta's operation of their upstream storage reservoirs. Sufficient historic data exist to assess the range of possible regulated river flows for different periods within an irrigation season, which could permit the synchronization of Bow River diversions into the WID headworks canal with water use and balancing of the internal storage reservoirs within the district. A project being conducted by a team of researchers from the University of Alberta is addressing this issue and developing a new set of modeling tools to combine the MTO approach with seasonal forecasts. It will produce the first seasonal operational model that relies on mathematical optimization.

Conclusions and recommendations

This paper discusses the importance of computer modeling in river basin management, particularly in terms of the sizing of proposed infrastructure to satisfy increased future water demands. Two solution strategies that use optimization algorithms were examined and compared: single time step (STO) and multiple time step (MTO) approaches. The multiple time step solution provides two important benefits: 1) optimization of both water demand and water supply simultaneously, and 2) development of optimal reservoir operating rules for each hydrologic year. The study also reveals the need for more stakeholder participation in water management through conducting regular audits of modeling results produced by third parties and regulatory agencies, especially if modeling results are used in decision making and affect long-term decisions related to future operations or infrastructure investments. It also demonstrates the need to revisit the current definition for failure criteria in light of the weekly distribution of deficits produced by the model. Previous attempts have not addressed weekly distributions of deficits in defining irrigation failures, which were based exclusively on annual deficits. The WEB.BM model used to obtain the MTO solutions in this study has recently been placed online and can be accessed at www.optimal-solutions-ltd.com.

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