ABSTRACT: This paper presents the methods and results of a project to develop a drought management tool for the City of Rocky Mount, North Carolina. The technique involves the generation of multiple, equally-likely, one-year streamflow forecasts (traces) based on current streamflow conditions. Using present starting conditions, the traces are run through a model that simulates system performance for each. If the probability of system failure is unacceptable, the user can re-run the simulation using a different minimum release regime and/or reduced demand level. The tool can thus be used to aid in the decision of when, or if, demand reductions should be imposed and what the magnitude of the reductions should be. During a simulation of the 65-year period of record using current demands, the model correctly identified the six serious droughts in time to take appropriate action. Equally important, there were no “false alarms” (i.e., predictions of a drought that did not materialize) over the same period. The simulated performance of this technique during past droughts is presented, and its use in the larger context of risk-based reservoir management is discussed.

INTRODUCTION

The drought of 1993 caused concern among officials in the City of Rocky Mount, a community of 50,000 in the coastal plain of North Carolina. Even though the drought did not appear to be particularly severe and demand was not extremely high, the reservoir dropped on the order of ten feet below the spillway (to approximately 25 percent of storage remaining), lower than ever before. A study to review the yield of the Tar River Reservoir and consultation with the city’s retained engineering firm led to discussions about new sources of raw water. The Roanoke River, some 35 miles distant, was identified as the most feasible next step in expanding the city’s water supply. The cost of developing this source was estimated at $70 million, which was considered prohibitive.

Water Resources Management, Inc. (WRMI) was contacted in late 1995 concerning the possibility of developing real-time operating tools that might ameliorate the impacts of future droughts and forestall, at least temporarily, the need to undertake the Roanoke River project. The work described here was begun in the summer of 1996.
The project had two main objectives. The first was the development of a computer model to assist the City in the management of the supply/demand balance during future droughts. The second was a reassessment of the reliability of the Tar River Reservoir. A single model, the Tar River Reservoir Operations Model, served both objectives. It has two operating modes -- Long-Term Simulation and Real-Time Operations -- both of which run on a weekly time step. Real-time drought management is accomplished primarily through the use of the Real-Time Operations mode, which provides probabilistic information about future inflows and storage levels given demand projections, the required minimum release, and a user-specified operating policy. It also predicts the likely effect of reductions in demand and/or minimum release.

The Long-Term Simulation mode allows the testing of candidate operating policies (reductions in demand and/or minimum release and the conditions that trigger them) over the period of hydrologic record. If a proposed policy would have worked well during past droughts, one has increased confidence that it will work acceptably well in the future. It was hoped that by using the model iteratively to investigate different operating policies, the City would be able to craft a drought management policy that achieved an appropriate balance between the risk of system failure and the hardship associated with the imposition of demand restrictions. The Long-Term Simulation mode was also used to reassess reservoir reliability, but that analysis is not discussed here.

**FORECAST GENERATION**

When making a forecast, it is important to know what is most likely to happen in the future. But, it is just as important to estimate the range of possible events and to be able to assign probabilities to the extremes. In the Tar River at Rocky Mount, the most likely forecast is almost always that the water supply will be sufficient. While this may be comforting, it is also important to know when there is a 10 percent chance that the water supply will not be sufficient, or a 5 percent chance, or a 1 percent chance. If the probability that a problem will occur is low enough, it will be appropriate to take no action. But as the risk rises, actions such as water use restrictions may be required to reduce the risk to lower, and more acceptable, levels. The forecast techniques used in this project are designed to produce forecasts that allow this type of estimation of risk.

The river forecasts used in both the Long-Term Simulation and the Real-Time Operations versions of the model are based on this simple fact -- when river flows have been low, they tend to remain low, and when river flows have been high, they tend to remain high. This is so because of the buffering effect of soil moisture and groundwater. Even after some precipitation, if conditions have been dry, streamflows will be somewhat diminished until soil moisture returns to more normal levels. Conversely, if it has been wet, streamflows will remain high ever after precipitation stops until soil moisture is reduced. This persistence in streamflow (i.e. the tendency to remain high or low) is estimated using statistical methods developed by R.M. Hirsch (1978 and 1982). The formula for predicting next month's streamflow is similar to the following:

\[
flow_j = a * flow_{j-1} + b * flow_{j-2} + c * flow_{j-3} + \ldots + C + E
\]

where

- \(flow_j\) is next month’s streamflow,
- \(flow_{j-1}\) is this month’s streamflow (already known),
- \(flow_{j-2}\) is last month’s streamflow, etc.,
- \(C\) is a constant, and
- \(E\) is an error term.
The parameters $a$, $b$, $c$, and $C$ are derived by regression to minimize the sum of the $E$ terms (squared) for the entire record. (In the actual forecast techniques, logarithmic transforms are used in place of the raw data.) Different $a$, $b$, $c$, and $C$ terms are derived for each calendar month (i.e. for January, for February, etc.). Hirsch’s methodology uses as many as six of the prior months (i.e. j-1 through j-6) in the formula in order to get the best fit. If a forecast is made with the $E$ term set to 0, then the result is the expected value of next month’s flow. The $E$ terms associated with each month in the historical record can be derived by comparing the expected value of flow in that month (the value of the formula with no $E$ term) with the actual flow for that month. The result is a time series of forecast errors for the period of record. Each monthly error represents the deviation from what would have been expected in that month.

A multi-month forecast can be made by forecasting next month, and then using the forecasted inflow for next month to generate a forecast for the month after next, and so on. If the $E$ terms are all set to 0, then the result is the expected value, i.e. the most likely forecast. This is what we would expect if the future weather was "average." But, the expected value alone is likely to indicate sufficient water to meet demands, and it will not allow us to estimate risks.

To estimate risks, we need a range of forecasts, which is produced as follows. Assume, for the example, that it is the end of May. If we wanted to know what would have happened if the weather in 1993, a dry year, repeated from the beginning of June on, we use the forecast equation starting with the current month’s flow (May), last month’s flow (April), March’s flow, and so on. We also use the error term for the month of June, 1993. Remember that the error term for June, 1993, represents the departure from "average" conditions for that month. Given the forecasted June flow, we repeat the calculation with that flow and the error from July 1993 to get the July forecast, and so on through November. The result of this process is the time series of flows that would occur in the immediate future if 1993 weather repeated.

Weather is very hard to predict, however, and a repeat of 1993 weather is no more likely than a repeat of, say, 1948 weather, or of any other year's weather. So if we generate a forecast using the error terms from any particular year, the result is as likely to occur as the forecast made using the error terms from any other year. The forecasting procedures used for this project generate a separate forecast for every error series in the record, i.e. one starting in June of each year for the example case. They are all "equally likely" and it is reasonable to estimate the probability of any one as $1/(n+1)$, where $n$ is the number of years in the record.

To do the long-term simulations, 64 forecast traces, each 52-weeks long, have been computed for every week in the historical record using the techniques described above. Each of these traces represents what would result if the rainfall sequence for that particular year were to occur beginning on the forecast date. In other words, different year’s rainfall patterns are superimposed on the current starting conditions, which is why they are known as conditional forecasts. The 213,696 forecasts (3339 weeks x 64 traces) are archived and available for use by the Long-Term model. When another year is added to the streamflow record, the set of long-term forecasts can be updated.

In order to run the Real-Time model, the forecasts must be made when the model is run. The model first produces equally-likely forecast traces for the next 12 months. The 10 worst (driest) of these are selected for simulation. The ranking to determine the worst 10 is based on the total volume of flow over the “forecast horizon.” (The forecast horizon, described below, is defined by the user and is an integral part of an operating policy. It should not be confused with the length of the forecasts, which is always 12 months.) To simulate what would happen if one of these traces actually occurred, we must make forecasts on forecasts. Thus, for each week in each
of the 10 selected traces, we repeat the forecast procedure in order to produce the forecasts that operators would have if that trace actually occurred. When the 10 simulations are complete, they each produce an estimate of what could occur if a historical drought were to recur. Thus, they allow us to estimate the risk of adverse consequences for water supply.

The skill of this technique is easy to demonstrate. Figure 1 shows the probability of any given reservoir elevation in mid-September based on streamflows through July 16 in two different years. The spring of 1992 was relatively wet whereas 1993 was dry. In both years the reservoir was full at the time the forecasts were made. The figure shows a clear difference between the years and represents a quantification of how much wetter than normal the spring of 1992 was and how much drier was the corresponding period for 1993. Simply being able to quantify the range of possible outcomes is a great step forward and, in a strange way, comforting for system operators.

This technique can be compared with another commonly used approach in which a simulation is performed using each year’s historical inflow beginning July 17. This approach assumes that July’s streamflow is independent of June’s, and thus makes no allowance for current soil moisture conditions. Because the reservoir was full on July 17 of both years, this technique would produce identical assessments of the likelihood of future conditions for both years.

**USING THE FORECASTS**

To make use of the forecasts, the model needs an operating policy. This policy will adjust the demand and/or minimum release depending upon the forecasted inflows. The components of a
policy are: risk factor, forecast horizon, trigger level, demand reduction, and minimum release reduction. In general, the policy works as follows. For each week, if current storage plus the forecasted inflow less the projected demand and the minimum release will cause the reservoir to fall below the trigger level, then the demand and minimum release will be reduced by the specified percentages. (As explained below, the forecasted inflow is dependent upon the risk factor and forecast horizon selected.) The model then does the simulation for the week and goes on to the next week. In the Long-Term Simulation mode, the historical, rather than the forecasted, inflow for the week is used in the simulation. Thus, for long-term simulations, the forecasts are used to determine whether or not to impose restrictions, but the historical inflow is used for operations. In this manner, a past drought can be simulated using the forecasts that would have been available at the time.

The model, however, must evaluate the policy conditions based on a single forecast, which is determined by the risk factor. The risk factor is the desired percentile of the flows ranked from driest to wettest. In other words, if a 5 percent risk factor is chosen, the fourth-driest forecast is used. (0.05 \times 64 = 3.2, which is rounded up to the fourth driest forecast.) A 1 percent risk factor would use the driest forecast over the forecast horizon. Thus, the risk factor is a measure of the operator’s aversion to risk. Whereas the risk factor is constant for any given long-term simulation, in an operational setting it would probably change over the course of a drought. It is likely, for example, that operators would be willing to accept, say, a 25 percent chance or falling to one-half full but only a 5 percent chance of falling below one-quarter full.

The forecast traces are rank-ordered based on the total inflow for the forecast horizon, which can be from 1 to 12 months. In reality, no drought in the region has lasted longer than six months, so forecasts for longer periods are not likely to be of much value. The historical rainfall sequence that produced the lowest flow for one month, however, will probably not produce the lowest flow over a period of several months. Therefore, a great deal of experimentation was required to identify an operating policy that achieves the City’s objectives and works well over the entire period of record.

Whereas in the Long-Term Simulation mode the inflows are known (i.e., the historical record), for Real-Time Operations the future flows are not known, and the simulation must be performed using forecasted inflows. We expected to do the real-time analysis as noted above, where 10 simulations were performed using the 10 driest forecasts for the selected horizon. However, for the Tar River Reservoir, an operating policy based on the second-order forecasts did not prove to be beneficial. This is undoubtedly because of the flashy nature of the reservoir, which can be nearly emptied and then refilled in three months time. This decision cycle is too short for forecasts on forecasts to be of any practical value. Instead, the model is run with each of the 64 traces. The results for 4, 8, 13, etc., weeks into the future were collected and sorted, resulting in a probability distribution of reservoir stage for those future dates. This gives the operators an estimate of the likelihood of adverse conditions occurring at various times into the future.

RESULTS

Through trial and error, a forecast-based operating policy comprised of the following parameters was identified as producing the best balance between risk and the imposition of restrictions: risk factor = 20%; forecast horizon = 2 months; trigger stage = 115 feet; and demand and minimum flow reduction factors = 10% and 25%, respectively. (Elevation 115 represents approximately 25 percent of usable storage remaining.) Figures 2 and 3 show a comparison of two Long-Term runs, one using this operating policy and the other without. The period shown is 1993, which, as
Figure 2. Restrictions Triggered

Figure 3. Effect of Restrictions on Reservoir Stage
noted, was the drought of record in the region. The simulated demand was 20 million gallons per day (mgd), approximately 6 mgd greater than the actual demand in 1993. These plots show that both the beginning and the end of the drought were detected early and that the imposition of restrictions for slightly less than three months saved over five feet (25 percent) of the available storage in the reservoir.

Over the period of record, this policy identified all of the serious droughts. At current demand levels, restrictions would have been imposed a total of six times, with no false alarms. By running the model in Real-Time mode for each week for each of these droughts, operations were simulated using the forecasts that would have been available at the time. Storage levels were updated each week using demand and minimum release levels dictated by the operating policy and the actual historical inflow. Thus, operational decisions were based on forecasts, and end-of-week storage levels were updated based on the inflow that actually materialized. This technique mimics perfectly the environment in which water supply managers operate.

Figures 4 through 7 show the model results for five different weeks during the drought of 1993. Because the selected trigger (20 percent chance of falling to elevation 115 two months in the future) involves looking two months ahead, only the probabilities 8 weeks into the future are shown. The trigger point is marked on each plot, and progress towards the trigger is clearly evident. By August 28 (Figure 7), the trigger has been met, indicating that restrictions should be imposed. Assuming that it takes a week to get restrictions implemented, by September 4 (Figure 8) the risk of falling below elevation 115 is 38 percent. Figure 8 also shows the forecasts for September 4 with the minimum release reduced to 60 cubic feet per second (cfs) and demand reduced by 10 percent. Note that the probability of reaching elevation 115 two months into the future (the trigger) has been reduced from 38 to 15 percent.

Table 1 shows the number of weeks over the period of record that restrictions would have been in place using the demand levels projected for the years 2000, 2010, and 2020 (16, 19, and 22.5 mgd, respectively). Note how the drought of 1993 is the worst under all demand levels in terms of reservoir drawdown but not in terms of the number of weeks of restrictions. The ranking in terms of weeks of restrictions also varies depending upon demand level. These phenomena are not unexpected and are the result of the interaction of the date of the onset of the drought relative to the City’s demand pattern and the extent to which inflows are lower than normal. (At higher demand levels, shorter, more intense droughts become relatively more severe than more protracted but less intense events.)

The State-mandated minimum release from the reservoir is 80 cfs. This release, which pre-dates the Clean Water Act, is 20 cfs higher than the flow upon which National Pollutant Discharge Elimination System (NPDES) permits are based. Hence the 20 cfs (25 percent) reduction in minimum release included in the recommended operating policy. Because the City’s demand is only slightly more than 20 cfs, a reduction in the minimum release from 80 to 60 cfs would have the effect of resolving the City’s short-term dilemma. Negotiations with State regulators are underway concerning the conditions under which such a reduction would be approved. The City anticipates that a concurrent reduction in demand will be required and is actively pursuing the development of a conservation plan that can be tied to the trigger level identified with the model. In addition to demand reduction, the City is also considering the acquisition of a depleted quarry to provide additional emergency storage. Pumping from the quarry would also be tied to the model. For its part, the State is balancing the relatively short and infrequent reductions in release against the costs, both economic and environmental, of developing a new source of supply. There is every expectation of a successful resolution to the issue without the need for additional capacity. More than likely, the revised permit will require that the Tar River Reservoir
Figure 4.

Figure 5.
Figure 6.

Figure 7.
Figure 8. Effect of Restrictions on Stage Probability

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<td>Demand Year and mgd</td>
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<td>9/6   8/30  8/30</td>
<td>117.5 116.7 115.2</td>
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<td>13    13    13</td>
<td>9/4   9/4   9/4</td>
<td>116.1 115.0 112.6</td>
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Table 1. System Performance
Operations Model be used determine whether an agreed-upon trigger has been met and, if so, to allow the minimum release to be reduced concurrently with the implementation of demand reduction measures.

REFERENCES
