CHAPTER 7

Representing Decision Processes

Decisions processes are the glue that binds together the information and material flow networks in an organization. Decisions about what information to collect and how to process it determine how information flows into an information network at the points where this network originates on the material flow network. Similarly, decisions about how to use information and what actions to take on material flows determine how information will impact those material flows at points where the information network points into the material flow network. Thus, a critical aspect of creating useful simulation models is appropriately modeling decision processes.

Increasingly, decision making is automated as computers take over more routine decision making activities in business processes, but many decisions continue to be made by humans. Thus, it is necessary to model human decision making if a realistic model is to be constructed of a process. This may seem like an overwhelmingly complex undertaking. How can we hope to mimic the subtle nuances of the human mind? Surely this is a task beyond the capabilities of a computer model!

This chapter presents research results about human reasoning, and then considers how to model decision making in a simulation model. As we shall see, the research results strongly support the conclusion that human decision making is neither particularly complex nor particularly effective. This somewhat discouraging result does, however, carry an optimistic message for those interested in modeling and improving business processes: It is possible to model human decision making with relatively simple models, and it is also possible to improve on unaided human decision making with systematic decision policies.

7.1 Experts and Expertise

This section summarizes key points in Chapter 10, Proper and Improper Linear Models, of Dawes (1988). That chapter presents results of research on the ability of experts to provide accurate intuitive predictions. The research results strongly support the conclusion that experts are *not* good intuitive predictors and that simple models using the same predictor variables as the experts provide more accurate predictions. Page references with the following quotes refer to Dawes (1988) unless otherwise noted.

Research Findings

A large number of studies have addressed the question of whether trained experts intuitive global predictions are better than statistically derived weighted averages (linear models) of the relevant predictors. Dawes notes (pp. 205 6), This question has been studied extensively by psychologists, educators, and others interested in predicting such outcomes as college success, parole violation, psychiatric diagnosis, physical diagnosis and prognosis, and business success and failure In 1954 Meehl summarized approximately twenty such studies comparing the clinical judgment method with the statistical one. *In all studies, the statistical method provided more accurate predictions, or the two methods tied.* Approximately ten years later, Jack Sawyer reviewed forty-five studies comparing clinical and statistical prediction. Again, there was *not a single study* in which clinical global judgment was superior to the statistical prediction.

Continuing, Dawes says (pp. 207 8), The finding that linear combination is superior to global judgment is strong; it has been replicated in diverse contexts, and *no* exception has been discovered Meehl was able to state thirty years after his seminal book was published, *There is no controversy in social science which shows such a large body of qualitatively diverse studies coming out so uniformly in the same direction as this one* People have great misplaced confidence in their global judgments.

The referenced work compared statistically derived weighted averages of relevant predictors, however, Dawes (pp. 208 9) himself investigated the possibility that *any* linear model might outperform experts. While, as he notes, the possibility seemed absurd, he found in several studies that linear models where the weights were selected randomly except for sign outperformed the experts and did almost as well as those with statistically derived weights.

Discussion of the Research Findings

When first studying these research findings, they may appear to say that experts can be replaced by simple linear equations (with random weights, no less!). However, closer consideration of the research shows that this is too strong a conclusion to reach from the research. Dawes (1979) notes, The linear model cannot replace the expert in deciding such things as what to look for, it is precisely this knowledge of what to look for in reaching the decision that is the special expertise people have. [However,] people especially the experts in a field are much better at selecting and coding information than they are at integrating it.

Dawes proposes (pp. 212-215) that the findings can be explained by a principle of nature, a mathematical principle, and a psychological principle. The *principle of nature* that Dawes states is that interactions among predictor variables tend to be monotone in many situations of interest. That is, while there may be interactions among predictor variables, these interactions do not change the monotonicity between a particular variable and the prediction [i.e., more of the predictor variable always predicts more (less) of the predicted variable regardless of the levels of the other variables].

The related *mathematical principle* is that interaction effects among variables which contribute monotonically to the overall effect can often be ignored and the resulting linear model will still provide adequate predictions, and also that specific coefficients for predictor variables are not as important in determining the results of a linear model as the signs of these coefficients. (While Dawes terms this principle *mathematical*, it is really an empirical statistical observation concerning real world data since counterexamples can be constructed.)

The *psychological principle* explaining the superior predictive ability of linear models is that people have difficulty integrating more than one variable. Thus, they tend to anchor on a particular predictor variable while making a prediction and do not adjust their predictions sufficiently to account for other variables. Linear models, of course, give constantly proportional attention to all variables.

Dawes concludes (p. 215), Given that monotone interactions can be well approximated by linear models (a statistical *fact*), it follows that because most interactions that do exist in nature are monotone and because people have difficulty integrating information from noncomparable dimensions, linear model will outperform clinical judgment. The only way to avoid this broad conclusion is to claim that training makes experts superior to other people at integrating information (as opposed, for example, to knowing what information to look for), and there is no evidence for that. There is no evidence that experts *think differently* from others.

He further comments (pp. 215 219), The conclusion that [linear models] outperform global judgments of trained experts is not a popular one with experts, or with people relying on them Experts have been revered and well paid for years for their it is my opinion that judgments As James March points out, however, such reverence may serve a *purely social function.* People and organizations have to make decisions, often between alternatives that appear equally good or bad. What better way to justify such decisions than to consult any intuitive expert, and the more money she or he charges, the better

But there is also a structural reason for doubting the inferiority of global judgment When we construct a linear model in a prediction situation, we know exactly how poorly it predicts. In contrast, our feedback about our global judgments is flawed. Not only do we selectively remember our successes, we often have *no knowledge* of our failures [For example, considering judgments on accepting or rejecting graduate school applicants], who knows what happens to rejected graduate school applicants? Professors have access only to accepted ones, and if the professors are doing a good job, the accepted ones will do well exonerating the professors judgments

In contrast, the systematic predictions of linear models yield data on just how poorly they predict. For example, in [one] study only 18% of the variance in longevity of Hodgkin s disease patients is predicted by the best linear model , but that is opposed to 0% by the world s foremost authority. Such results bring us abruptly to an unpleasant conclusion: a lot of outcomes about which we care deeply are not very predictable We *want* to predict outcomes important to us. It is only rational to conclude that if one method (a linear model) does not predict well, something else may do better. What is not rational is to conclude this something else is intuitive global judgment.

Concluding Comments on the Research Findings

The research discussed above carries an optimistic message for those of us who work on quantitative models. Even simple quantitative models can outperform experts in prediction tasks. However, the research also points out that experts play a key role in developing such models: They are needed to identify the key variables to incorporate into a model.

The research also carries a cautionary message for those working on developing computer-based expert systems. The generally stated criterion for judging the effectiveness of such systems is how well they replicate the performance of an expert. However, the research indicates that at least in prediction tasks it is possible with even simple models to outperform experts *once the key predictor variables have been identified*. Thus, the performance of experts may not be a good benchmark for judging the performance of a computer-based expert system. It is probably possible to do better.

As a final comment, I return to the quote from Dawes at the end of the last subsection. While he notes the superiority of linear models over expert judgment, he also notes that these models don t do a particularly good job either in many situations. Often, better models are available, especially when physical system performance is of interest. For example, someone predicting the behavior of a new airplane that has not yet been built would not use either expert judgment or a simple linear model. The physical principles which govern the behavior of an airplane are well known, and a detailed quantitative model would be built to predict the performance of the airplane long before it was built.

7.2 Modeling Decision Processes

The remainder of this chapter presents structures that can be used to represent decision making processes within a simulation model. Specifically, we consider decisions at points where information arrows enter flows. These junctions are key decision making points within an organizational process because they are where information impacts the physical activities of the process.

Example: Managing Flows Through the Thurabond Dam

We will proceed by considering a management decision process with a simple structure: Managing the outflow from a water reservoir. While it is not likely that most readers need to manage the outflow from a reservoir, this decision situation has two characteristics that make it a useful example for models of decision processes. First, the stock and flow variables are graphically obvious: The amount of water in the reservoir is clearly a stock, and the flows into and out of the reservoir are clearly flows. Second, it has a relatively simple structure where the implications of different decision rules can be easily seen. In many business settings, there are several interacting stocks and flows, and thus the impact of changing a single decision rule may be obscured by the complexities of the situation. This example is inspired by one in Roberts, et al (1983), Chapter 22.

The Rappanno Valley has ideal growing conditions for several different types of vegetables, but very little rain. During the waning years of Senator Thurabond s distinguished Congressional career, Federal funds were allocated for the construction of the Thurabond Dam in Big Stormy Gorge on the Callahali River. This dam, together with the Rappanno Valley Irrigation Project, established an extensive irrigation system throughout Rappanno Valley, and in the forty years since the completion of the dam and irrigation system, a prosperous agricultural community has developed there.

The essential features of the reservoir and irrigation system are shown in Figure 7.1. The inflow to Big Stormy Reservoir behind Thurabond Dam is not under our control, and the amount of water in the reservoir is labeled Reservoir Contents. All releases from the reservoir flow into the Rappanno Valley drainage basin where the water is primarily used for agricultural purposes. The amount of water available in the drainage basin at any time for agricultural purposes is labeled Drainage Basin Contents. Water is consumed from the Rappanno Valley drainage basin in a variety of ways, including transpiration from plants, evaporation, and drainage. For notational simplicity, we refer to all of these losses as drainage. This drainage is not under the control of the Thurabond Dam operator. Thus, there is only one decision variable, the release through Thurabond Dam, which is shown in the center of Figure 7.1.

We will examine decision policies for managing releases through Thurabond Dam for use in Rappanno Valley agriculture. The Dam impounds water from an substantial stretch of the Callahali River, and the average net annual impoundment, taking into account evaporation losses, is 0.5 million acre-feet. Standard

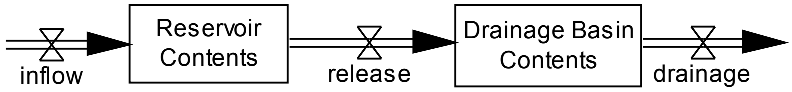


Figure 7.1 *Water flow process*

operating procedure at Thurabond Dam is to maintain a long term average of one million acre-feet of water behind the dam in Big Stormy Reservoir, although the actual amount of water in the reservoir may vary over the short term depending on rainfall and other conditions. Not surprisingly, agriculture has expanded in the Rappanno Valley to consume 0.5 million acre-feet per year of water. More specifically, the drainage system within the Valley holds one million acres-feet of water accessible for agricultural use, and fifty percent of this is consumed each year.

A reservoir system can have several purposes. The rainy season in a region may not coincide with the growing season, and then a reservoir can be used to time shift water from the rainy season to the growing season. If there is flooding in an area, then the reservoir can trap water during periods of high flow and gradually release it over an extended period of time. If there are periods of drought, then the reservoir can save water over several years and release it during drought years.

The primary purpose of Big Stormy Reservoir is to hold water that would otherwise flow unused down the Callahali River to the ocean about two hundred miles away, so that this water can be used for agriculture. Our analysis of operating policies for releases through Thurabond Dam will focus on maintaining sufficient flow to support agriculture in the Rappanno Valley, while assuring that there is sufficient reserve in Big Stormy Reservoir to continue to support agriculture through a drought period, and also assuring that water does not build up in the reservoir to the point where it threatens to overtop Thurabond Dam.

It is important to note that in this situation, as in any process involving flow of material, the flowing material must be *conserved*. That, is the total amount of material that flows into the process must, over the long run, average out to the same amount that flows out of the process. Otherwise, material will indefinitely continue to pile up somewhere in the process and you will ultimately run out of storage capacity. Since there is a sequential flow of water through the process shown in Figure 7.1, the requirement that material must be conserved means that the long run averages for inflow, release, and drainage must all be the same.

Types of Decision Models

The discussion about experts earlier in this chapter shows that even experts in a field use relatively simple decision procedures. Therefore, it is often appropriate to use simple models to represent decision processes in simulation models. There are two primary issues that must be addressed in constructing such models: 1) What factors should be taken into account in the decision model, and 2) How should these factors be combined. We investigate both of these issues below.

Many decision processes take into account multiple factors. For Thurabond Dam, it seems clear that any reasonable decision process for releases will need to consider both the level of Big Stormy Reservoir and the impact of outflows from the reservoir on agriculture in Rappanno Valley. In this case, and this is typical of many decision situations, there are explicit or implicit *goals* with regard to both of these factors. For the reservoir level: We do not want the quantity of water in the reservoir to become so large that a sudden increase in inflow might lead to the threat of overtopping Thurabond Dam. (In such situations, emergency releases must be made, which can lead to substantial downstream flooding.) We also do not want the water in the reservoir to get too low, because if a drought occurs when the reservoir is low we might not be able to provide sufficient water to the Rappanno Valley to support agriculture.

With regard to outflows: We do not want these to be too high or they will cause flooding in the Rappanno Valley, and we also do not want them to be too low because this could cause crop failure. One way to address this is to attempt to maintain a constant value for the contents of the drainage basis. If this gets too high, then flooding will occur, and if it gets too low, there will be insufficient water to maintain crops.

Thus, to summarize, our goals are to maintain constant levels for the two variables Reservoir Contents and Drainage Basin Contents in Figure 7.1.

One can visualize a variety of different quantitative forms for decision functions which address multiple goals. The two simplest are 1) an average of the factors, perhaps with different weights used for each factor, or 2) a product of the factors. These forms are both used in simulation models, and they have proved sufficient to model a variety of different real-world decision processes.

7.3 Weighted-average Decision Models

The ideas underlying a weighted-average decision model for a flow variable are straightforward and intuitively appealing:

1. A portion of the flow is being used to attempt to maintain some goal with respect to each of the decision factors, and if the flow deviates from what is needed to maintain that goal, then this portion of the flow should be adjusted.
2. These adjustments are made over a period of time (that is, averaged) in order to avoid disruptive discontinuities in operations, and also to smooth out transient shifts in conditions due to random factors.
3. The total flow is made up of a sum of the portions assigned to achieving each goal.

4 Different weights may be assigned to meeting each goal depending on their relative importance.

Figure 7.2a shows a stock and flow diagram to represent a weighted-average decision model for the release decision variable. This has been developed from the Figure 7.1 diagram by adding a variety of auxiliary variable, most of which are related to the release decision. In the upper left corner of the diagram, LONG TERM AVERAGE INFLOW is a constant which provides the average flow rate into Big Stormy Reservoir. From our earlier discussion, we know that this is 0.5 million acre-feet per year. This is used to set a target for the amount of water in Big Stormy Reservoir, which is indicated on the diagram by reservoir target. We will assume that the target is two times the LONG TERM AVERAGE INFLOW. That is, the reservoir is operated to maintain on average two years of inflow.

There is also a target for the amount of accessible water in the Rappanno Valley drainage system, which is indicated in the upper right corner of Figure 7.2a by DRAINAGE BASIN TARGET. This target is set to maintain a constant amount of water in the basin over the long term. As noted above, annual drainage from the valley is fifty percent of the accessible water in the basin. We also know from our earlier discussion that this average drainage must equal the LONG TERM AVERAGE INFLOW, which is 0.5 million acre-feet. Therefore, the DRAINAGE BASIN TARGET must be twice this, or one million acre-feet.

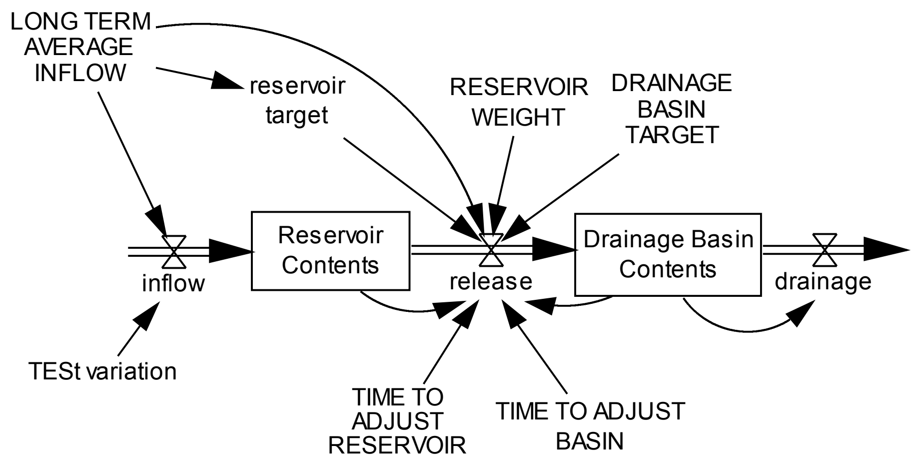
The two constants TIME TO ADJUST RESERVOIR and TIME TO ADJUST BASIN, which are shown in the lower center of Figure 7.2a, relate to the averaging period used to address deviations from the goals with respect to the reservoir contents and the drainage basin contents. Finally, the constant RESERVOIR WEIGHT in the upper center of the figure represents the weight assigned to the goal of maintaining a constant value for Reservoir Constant, relative to maintaining a constant value for Drainage Basin Contents.

As noted above, with a weighted-average decision rule, the flow is visualized as being split into several parts which add up to constitute the entire flow. A useful way to develop the decision rule is often to visualize the flow being controlled as made up of a base component needed to maintain stable conditions over the long run, and then correction terms needed to address deviations from each of the goals. For the reservoir, the long term average inflow to the reservoir is LONG TERM AVERAGE INFLOW, and therefore the base component of release must be equal to this.

The correction term for deviations from the target for the quantity of water in the reservoir can then be built up in three steps: First, note that this correction term should be zero when the value of Reservoir Contents is equal to reservoir target. Therefore, the correction term should be proportional to

$$\text{Reservoir Contents} - \text{reservoir target} \qquad (7\ 1)$$

That is, if there is more water in the reservoir than the target, then the release should be increased, while if there is less water than the target, then release should be decreased.



a. Stock and flow diagram

```
(01) drainage = 0.5 * Drainage Basin Contents
(02) Drainage Basin Contents = INTEG(release-drainage,
       DRAINAGE BASIN TARGET)
(03) DRAINAGE BASIN TARGET = 1
(04) FINAL TIME  = 4
(05) inflow = LONG TERM AVERAGE INFLOW+TEST variation
(06) INITIAL TIME  = 0
(07) LONG TERM AVERAGE INFLOW = 0.5
(08) release = LONG TERM AVERAGE INFLOW
      + RESERVOIR WEIGHT * (Reservoir Contents - reservoir target)
        / TIME TO ADJUST RESERVOIR
      +(1 - RESERVOIR WEIGHT)
        * (DRAINAGE BASIN TARGET - Drainage Basin Contents)
          / TIME TO ADJUST BASIN
(09) Reservoir Contents
      = INTEG(inflow - release, reservoir target)
(10) reservoir target = 2 * LONG TERM AVERAGE INFLOW
(11) RESERVOIR WEIGHT = 0.5
(12) SAVEPER  = TIME STEP
(13) TESt variation = STEP(0.1, 0.5)
(14) TIME STEP  = 0.01
(15) TIME TO ADJUST BASIN = 0.05
(16) TIME TO ADJUST RESERVOIR = 0.5
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b. Vensim equations

Figure 7.2 *Weighted-average decision rule*

However, if the expression in equation 7.1 were used as the correction term for deviations from the reservoir goal, this would mean that any deviation would be instantly corrected. This is probably not feasible due to physical constraints on the dam, and it may also not be desirable because every little random variation in reservoir level would result in fluctuations in the release. Thus, the correction will be averaged over a period of time as follows:

$$\frac{\text{Reservoir Contents} - \text{reservoir target}}{\text{TIME TO ADJUST RESERVOIR}} \tag{7 2}$$

This means that if the correction were to continue at the same rate, it would take a length of time equal to TIME TO ADJUST RESERVOIR to completely remove the deviation. (In actuality, the level of the reservoir will change over time, and thus the actual correction period will probably differ from TIME TO ADJUST RESERVOIR.)

Another way to visualize this is to define

$$\text{RESERVOIR ADJUSTMENT FACTOR} = \frac{1}{\text{TIME TO ADJUST RESERVOIR}}$$

and then equation 7.2 can be rewritten

$$\text{RESERVOIR ADJUSTMENT FACTOR} \times (\text{Reservoir Contents} - \text{reservoir target})$$

From this, we see that RESERVOIR ADJUSTMENT FACTOR is the portion of the deviation from the goal that is corrected each unit of time.

Finally, to complete the correction factor for the reservoir goal, the expression in equation 7.2 is multiplied by the RESERVOIR WEIGHT, which is a number between zero and one, to take into account the relative importance of this goal. This gives

$$\text{RESERVOIR WEIGHT} \times \frac{\text{Reservoir Contents} - \text{reservoir target}}{\text{TIME TO ADJUST RESERVOIR}} \tag{7 3}$$

A similar procedure can be used to determine the correction factor for the drainage basin goal, which is

$$(1 - \text{RESERVOIR WEIGHT}) \times \frac{\text{DRAINAGE BASIN TARGET} - \text{Drainage Basin Contents}}{\text{TIME TO ADJUST BASIN}} \tag{7 4}$$

Note that in this case, the actual level for the variable (Drainage Basin Contents) is subtracted from the goal (DRAINAGE BASIN TARGET) because we wish to decrease the flow if the actual level is above the target and increase it is the actual level is below the target. Note also that we are assigning weights to the two goals so that these weights add up to one. Therefore, it is not necessary to define a separate weight for the drainage basin goal: It must be equal to 1 – RESERVOIR WEIGHT.

The final complete expression for the release decision rule is obtained by adding the two correction terms in equations 7.3 and 7.4 to the long term average flow rate LONG TERM AVERAGE INFLOW. This yields

$$\begin{aligned} \text{release} = {} & \text{LONG TERM AVERAGE INFLOW} \\ & + \text{RESERVOIR WEIGHT} \times \frac{\text{Reservoir Contents} - \text{reservoir target}}{\text{TIME TO ADJUST RESERVOIR}} \\ & + (1 - \text{RESERVOIR WEIGHT}) \\ & \quad \times \frac{\text{DRAINAGE BASIN TARGET} - \text{Drainage Basin Contents}}{\text{TIME TO ADJUST BASIN}} \end{aligned} \tag{7 5}$$

The complete set of equations for the reservoir management model with a weighted-additive decision rule are given in Figure 7.2b. Equation 8 of this figure corresponds to equation 7.5 above. The values assumed for the various constants are also shown in Figure 7.2b. Note, also that equation 1 in this figure shows that the drainage is a proportion of the Drainage Basin Contents as discussed above.

As shown by equations 2 and 9 in Figure 7.2b, the initial values of Reservoir Contents and Drainage Basin Contents are set equal to the targets for these variables. Thus, so long as inflow continues to be equal to LONG TERM AVERAGE INFLOW, the entire process will be in steady state, and the levels of the two stocks will remain the same with a constant flow of LONG TERM AVERAGE INFLOW through the system. Referring back to Figure 7.2a for a moment, note that there are dashed arrows from reservoir target to Reservoir Contents, and also from DRAINAGE BASIN TARGET to Drainage Basin Contents. These dashed arrows indicate that the initial level for each of the levels depends on the specified variable, as shown by equations 2 and 9 of Figure 7.2b.

As a test input for this simulation model, we use a step, as shown by equations 5 and 13 of Figure 7.2b. The results are shown in Figure 7.3. The top set of graphs shows the results with a RESERVOIR WEIGHT equal to one, the middle set of graphs shows the results with a RESERVOIR WEIGHT equal to 0.5, and the bottom set of graphs shows the results with a RESERVOIR WEIGHT equal to zero. Thus, in the top and bottom sets of graphs, only one of the goals is taken into account in setting the reservoir release, while in the middle set of graphs both goals are taken into account. (Note that some scales on corresponding graphs in the three parts of Figure 7.3 differ.)

The pattern for release is substantially different for the three cases. When there is no weight on the reservoir goal (RUN0) the release remains constant at 0.5 million acre-feet per year, and the Reservoir Contents steadily grows to absorb the extra inflow that is not being released. When there is no weight on the drainage basin goal (RUN10) the release grows to 0.6 million acre feet per year to stabilize the amount of water in the reservoir, but the Drainage Basin Contents grows substantially.

Finally, in the case where the two goals are given equal weight (RUN5), the results are intermediate between the other two cases, but the values for Reservoir Contents and Drainage Basin Contents are closer to the RUN0 case than the RUN10 cases. The reason for this can be seen from examining the values for the two constants TIME TO ADJUST BASIN and TIME TO ADJUST RESERVOIR in equations 15 and 16 of Figure 7.2b. We see from these equations that TIME TO ADJUST BASIN is one-tenth of TIME TO ADJUST RESERVOIR (0.05 versus 0.5). Thus, adjustments to Drainage Basin Contents are made much more quickly than adjustments to Reservoir Contents, and hence the final results for the equal weight case are closer to the case where all the weight is placed on maintaining a constant value for Drainage Basin Contents. This illustrates that the overall performance of a weighted-average decision rule is equally impacted by the weights and the adjustment time constants.

7.4 Floating Goals

The decision model discussed in the last section assumes that long term averages are known and are stable, and therefore can be used in decision rules. What if these long term averages are not known? The model in Figure 7.4 shows one way to address this. The differences between the stock and flow diagram in Figure 7.4a and the one shown earlier in Figure 7.2a are in the upper left hand corner. A new variable short term average inflow has been introduced, and now this is used as an input to the release decision, rather than LONG TERM AVERAGE INFLOW.

This short term average inflow is calculated by smoothing inflow using a first order exponential smooth with a time constant of INFLOW AVERAGING TIME. Thus, this approach does not assume that the decision maker managing release has access to the values of LONG TERM AVERAGE INFLOW. This modeling approach is sometimes called floating goals because the goal is calculated from data generated as the model solves rather than being prespecified. Therefore, this goal can vary, or float as the data changes.

The equations for this model are shown in Figure 7.4b. These differ from the equations in Figure 7.2a as follows: Additional equations numbered 6 and 14 have been added to calculate short term average inflow.

The results of applying the floating goal decision rule are shown in Figure 7.5. The meanings of RUN0, RUN5, and RUN10 are the same in this figure as in Figure 7.3. Note that in this case when all the weight is put on the reservoir goal (RUN10) there is a somewhat counterintuitive result with respect to release. After the inflow to the reservoir jumps at time 0.5, the release actually drops for about a year. This is because the target for Reservoir Contents grows as the inflow to the reservoir grows, as shown by equation 11 of Figure 7.4b, and therefore more water is needed in the reservoir to meet the target.

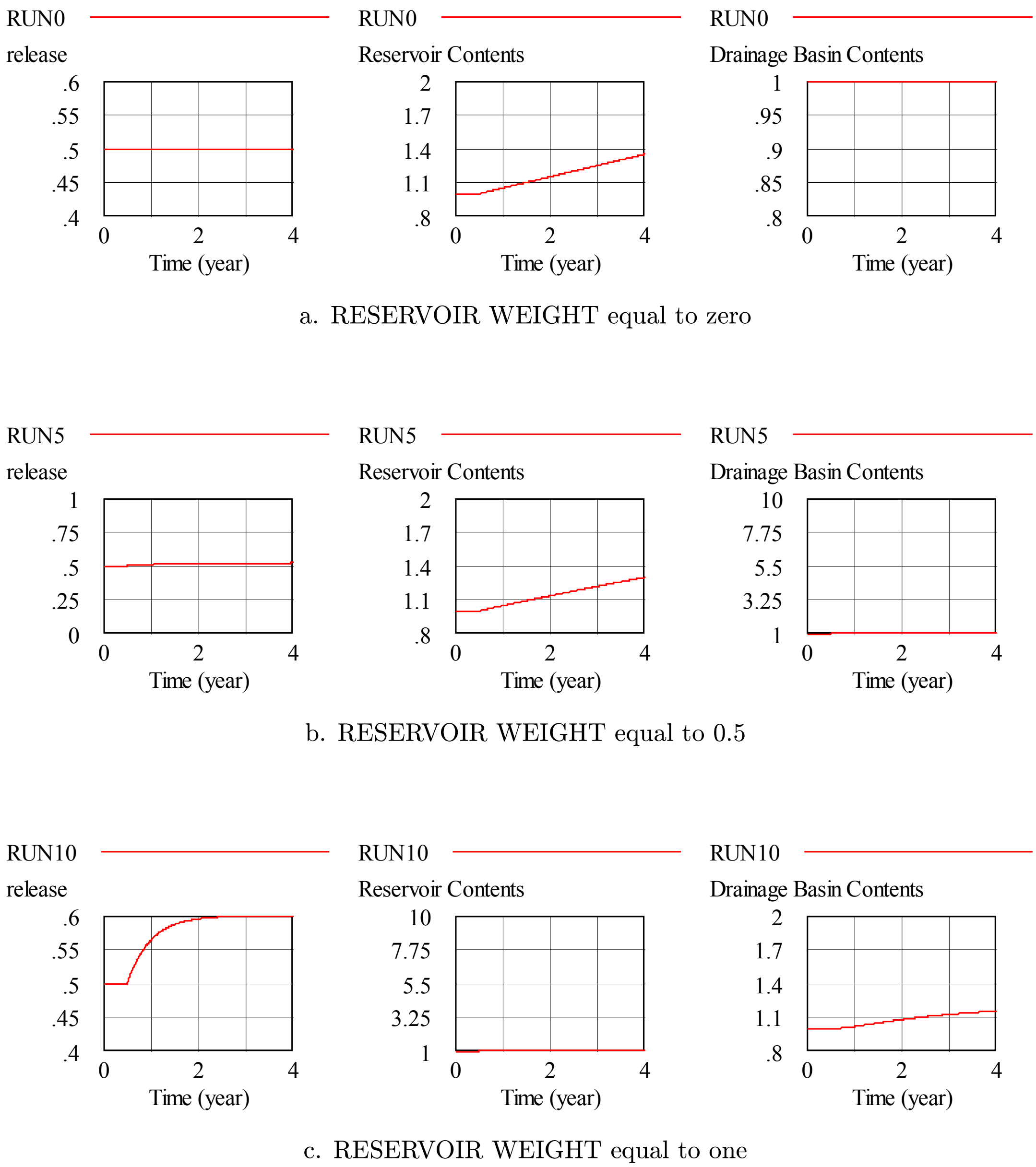
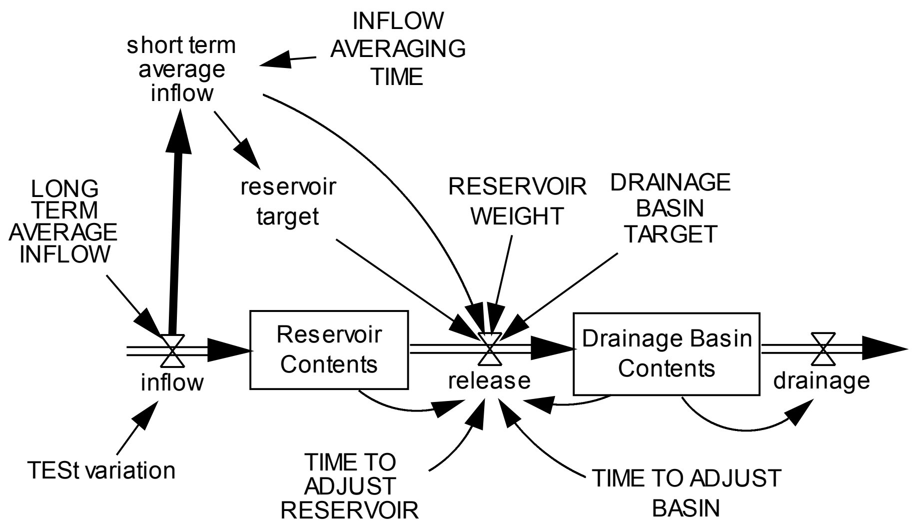


Figure 7.3 *Dynamics with weighted-average decision rule*



a. Stock and flow diagram

```
(01) drainage = 0.5 * Drainage Basin Contents
(02) Drainage Basin Contents
        = INTEG(release - drainage, DRAINAGE BASIN TARGET)
(03) DRAINAGE BASIN TARGET = 1
(04) FINAL TIME  = 4
(05) inflow = LONG TERM AVERAGE INFLOW + TESt variation
(06) INFLOW AVERAGING TIME = 0.5
(07) INITIAL TIME  = 0
(08) LONG TERM AVERAGE INFLOW = 0.5
(09) release = short term average inflow +
      RESERVOIR WEIGHT
         * (Reservoir Contents - reservoir target)
             / TIME TO ADJUST RESERVOIR
     +(1 - RESERVOIR WEIGHT)
         * (DRAINAGE BASIN TARGET - Drainage Basin Contents)
           /TIME TO ADJUST BASIN
(10) Reservoir Contents = INTEG(inflow - release, reservoir target)
(11) reservoir target = 2 * short term average inflow
(12) RESERVOIR WEIGHT = 0.5
(13) SAVEPER  = TIME STEP
(14) short term average inflow = smooth(inflow, INFLOW AVERAGING TIME)
(15) TESt variation = STEP(0.1, 0.5)
(16) TIME STEP  = 0.01
(17) TIME TO ADJUST BASIN = 0.05
(18) TIME TO ADJUST RESERVOIR = 0.5
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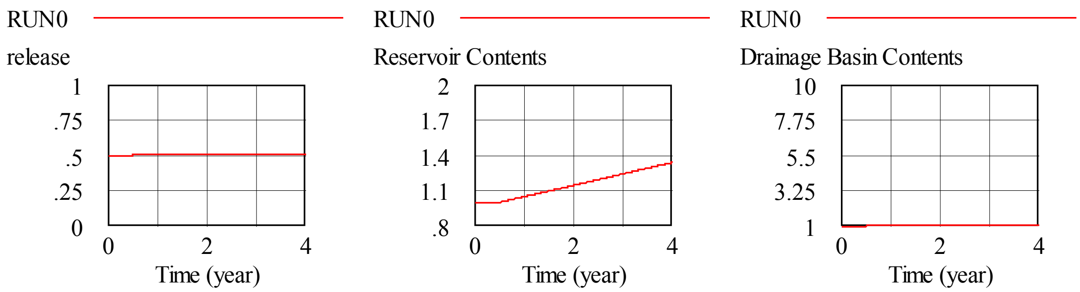
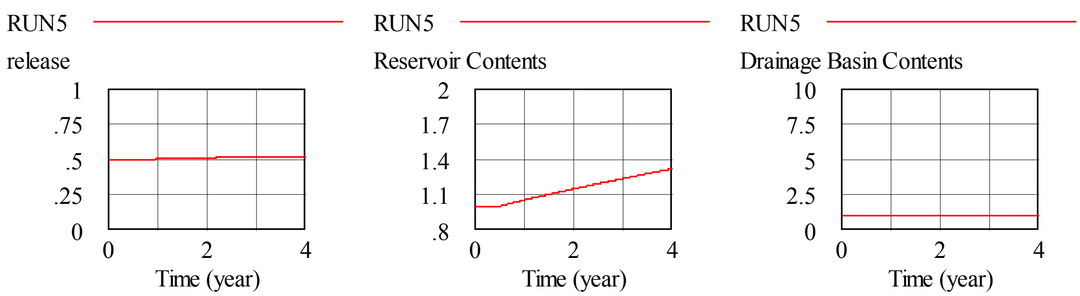
b. Vensim equations

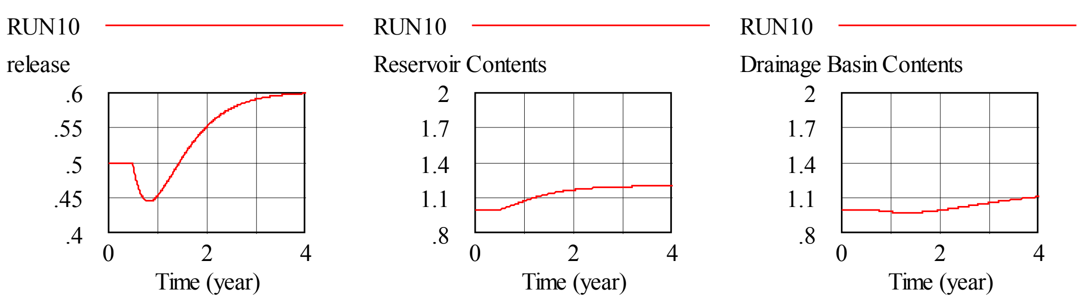
Figure 7.4 *Floating goal decision rule*



a. RESERVOIR WEIGHT equal to zero

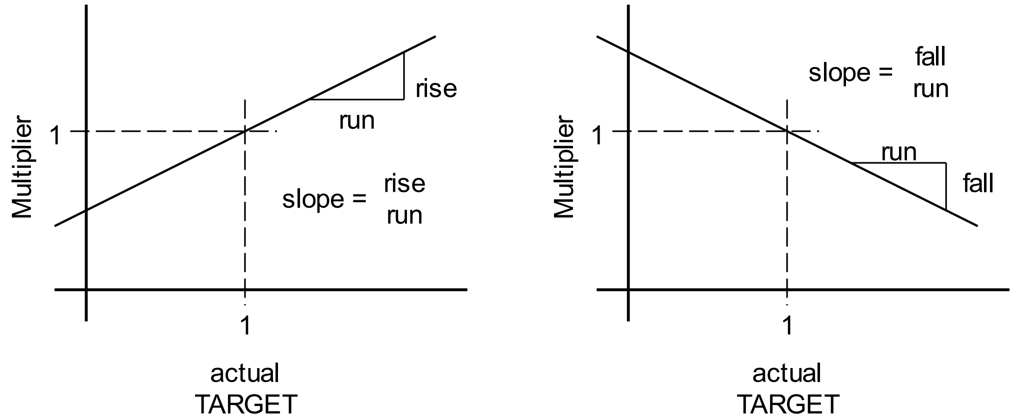


b. RESERVOIR WEIGHT equal to 0.5



c. RESERVOIR WEIGHT equal to one

Figure 7.5 *Dynamics with floating goal decision rule*



a. Increasing case   b. Decreasing case

Figure 7.6 *Multipliers*

7.5 Multiplicative Decision Rule

Another approach for modeling decision rules is to use a multiplicative form. With the weighted-additive form, correction terms are *added* to a base flow rate, while with the multiplicative form, correction factors are used to *multiply* the base flow rate. The correction factors are illustrated in Figure 7.6. The left hand graph in this figure applies to a situation where if the variable of interest is above its target (goal) value the flow needs to be increased. (This is the situation in the reservoir example for Reservoir Contents.) The right hand graph in Figure 7.6 applies to a situation where if the variable of interest is above its target value, the flow needs to be reduced. (This is the situation in the reservoir example for Drainage Basin Contents.)

It turns out to be useful to normalize the variables by dividing them by their target values, as shown in the Figure 7.6 graphs. When this is done, a situation where a normalized variable is equal to one will have a multiplier of one. That is, when the value of a variable is equal to its target value, there will be no correction applied to the base case flow.

The slope of the normalized curve, as defined in the graphs in Figure 7.6, then sets the strength of the reaction in the flow that occurs for a specified percentage deviation in a variable from its target value. The greater the slope, the greater the response for a specified percentage deviation of a variable.

It is straightforward to derive the equation for the multiplier as a function of the variable, its TARGET, and its slope. For the increasing case in Figure 7.6a, this is

$$\text{Multiplier} = \text{slope} \times \frac{\text{actual}}{\text{TARGET}} + (1 - \text{slope}) \qquad (7\ 6a)$$

and for the decreasing case in Figure 7.6b, this is

$$\text{Multiplier} = 1 + \text{slope} - \text{slope} \times \frac{\text{actual}}{\text{TARGET}} \qquad (7\ 6b)$$

The results of applying the multiplicative decision rule approach to the reservoir example are shown in Figure 7.7. (Note that this example is the multiplicative version of the weighted-average example in Figure 7.2. If desired, a floating goals approach can be applied to the multiplicative case in a manner analogous to that presented above for the weighted-average decision rule.) As in the weighted-average case, the base case flow is LONG TERM AVERAGE INFLOW. The targets for the reservoir and drainage basin are reservoir target and DRAINAGE BASIN TARGET, respectively. The slopes of the correction factors for these are RESERVOIR ADJUSTMENT SLOPE and DRAINAGE BASIN ADJUSTMENT SLOPE, respectively.

The stock and flow diagram for this decision rule is shown in Figure 7.7a, and the Vensim equations are shown in Figure 7.7b. Equation 9 of this figure shows how equation 7.6 is applied in this case to develop the multiplicative decision rule.

Figure 7.8 shows the results of running a simulation with the equations in Figure 7.7b.

The performance of the weighted-average and multiplicative decision rules will be similar for small variations from the desired flow, provided the constants in the two models are suitably adjusted. For larger variations, the multiplicative rule can lead to a more aggressive response than the weighted-average rule because the responses for the two variables interact in a multiplicative fashion. This type of decision rule may be appropriate for modeling some decision makers. However, the discussion above of the performance of experts indicates that an additive model will perform as well as many actual decision makers.

7.6 References

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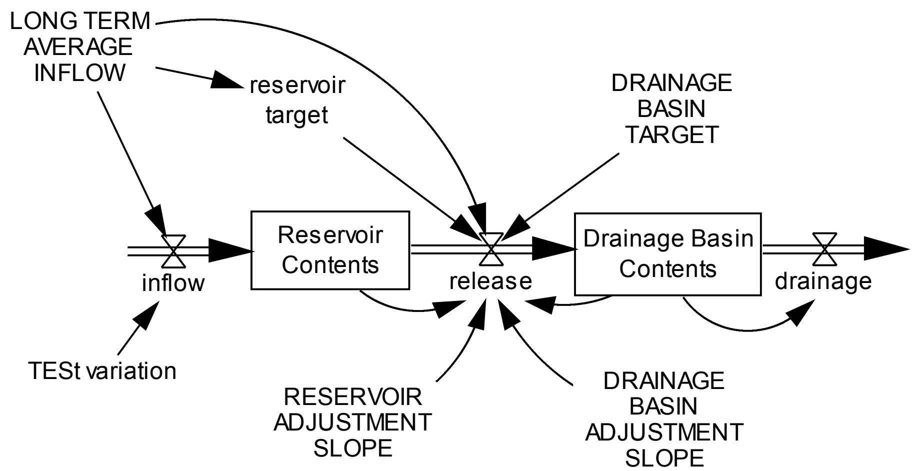

a. Stock and flow diagram

```
(01) drainage = 0.5*Drainage Basin Contents
(02) DRAINAGE BASIN ADJUSTMENT SLOPE = 1
(03) Drainage Basin Contents = INTEG(release-drainage,
       DRAINAGE BASIN TARGET )
(04) DRAINAGE BASIN TARGET = 1
(05) FINAL TIME  = 4
(06) inflow = LONG TERM AVERAGE INFLOW+TEST variation
(07) INITIAL TIME  = 0
(08) LONG TERM AVERAGE INFLOW = 0.5
(09) release = LONG TERM AVERAGE INFLOW
      *(RESERVOIR ADJUSTMENT SLOPE
        *(Reservoir Contents/reservoir target)
          +(1-RESERVOIR ADJUSTMENT SLOPE))
      *(1+DRAINAGE BASIN ADJUSTMENT SLOPE
        -DRAINAGE BASIN ADJUSTMENT SLOPE
          *(Drainage Basin Contents/DRAINAGE BASIN TARGET))
(10) RESERVOIR ADJUSTMENT SLOPE = 1
(11) Reservoir Contents = INTEG(inflow-release,reservoir target)
(12) reservoir target = 2*LONG TERM AVERAGE INFLOW
(13) SAVEPER  =
        TIME STEP
(14) TESt variation = step(0.1,0.5)
(15) TIME STEP  = 0.01
```

b. Vensim equations

Figure 7.7 *Multiplicative decision rule*

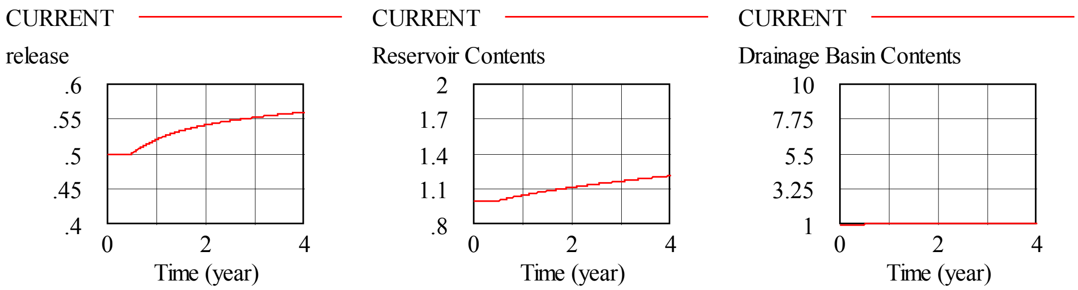

Figure 7.8 *Dynamics with multiplicative decision rule*