MODELING THE PROCESS OPERATIONS DECISION CYCLE: ECONOMIC IMPLICATIONS

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Abstract

The decision process in plant operations typically takes the following structure - detect, analyze, forecast, choose, and implement – with the cycle then repeated at the next decision interval. Modeling this decision cycle is a useful structure for analysis of some traditionally difficult economic questions. For example, what is the value of "better information," "more flexibility," or "improved integration" and the technologies that provide these qualities? That these attributes have value is widely accepted. However, quantification of the value has been difficult. This quantification is important if rational economic decisions are to be made about the correct level of investment and best technologies to support these characteristics and to be able to measure whether or not the investments achieved their objectives. Such potential system investments might include process models of greater fidelity, real time historians and other databases, "smart" instrumentation, improved data analysis software, and/or improved user interfaces. In this paper an economic model is proposed for estimation of the value of such investments based upon their effect upon the decision process in the plant. This model leads to quantitative estimates that have a realistic financial basis. An example is presented showing how the method can be applied.

Keywords

Process plant decision modeling, decision economics, technology investment valuation, information technology benefits, return on investment, ROI

Introduction

Many new system oriented technologies have been proposed for installation in the process industries. These technologies include software applications claiming advantages such as improved data analysis, better "knowledge" management, improved user interfaces for data visualization, better process modeling, improved group collaboration, etc. They also include hardware such as "smart" instrumentation, improved analytical devices, and upgraded plant networks. Each of these technologies has proponents claiming that their particular application will result in a very high return on investment and that it should be favored over the others. It is common to hear the claimed benefits resulting from their installation characterized by terms such as "better decisions"," more flexibility" and/ or "better integration".

But how can these benefits be quantified?

The management in a process plant always has limited capital and expense money to allocate. These new applications must compete for available funds with required regulatory and environmental investments, requests for new process equipment, new product developments, and training programs and systems. Which one or ones should be chosen for funding? Any non-mandated investment must produce measurable gains and these gains are compared in the investment evaluation as choices are made on which to fund. In addition, how much is it justified to spend on the technology – other than the amount requested by the technology vendor? When is the technology just too expensive?

To answer these questions, a realistic estimate of the expected financial return on these technology investments is needed. With this estimate the corporation can compare them against other potential outlays and make a rational choice for capital and expense allocation. An issue raised by these investments, and a common point of debate/ confusion, is that their value is only recognized when an actual decision is implemented. As stated above, what is the value of information that offers the *potential* to improve a decision/ plan? The question again is how can the concepts of "better decisions"," more flexibility" and/ or "better integration" be quantitatively valued? These are normally considered "soft" benefits not conducive to precise measurement.

Although it is common to model the equipment, reactions, and hydraulics in a process industries' plant, it is less familiar to model how these organizations function and how individuals within the organizations perform their activities. In this paper, the focus is on a particular class of decisions typically made by operations personnel – called the operations decision cycle. Modeling this decision cycle allows us to better understand qualitatively the effect of these technologies and to quantitatively estimate the expected future value of operational decisions with and without the new technology. By comparing these estimates the technology's financial impact can be assessed. This provides a basis for comparison and funding decisions.

Background and Previous Work

Among system applications, attempts to quantitatively estimate the benefits of modern information technology have been popular since the early days of its use. A search for books on Amazon.com on this subject at the time of preparation of this paper resulted in 55477 citations with almost 1000 in the last four years alone. A recent survey by Berghout (2001) identified over sixty distinct approaches to evaluating benefits. Some recent reviews would be the ones by Thorp (1999) and Digrius and Keen (2002). Not all of these commentaries are favorable towards IT investments, most notably the books by Paul Strassman (1997) who uses a macro economic approach to analyze their benefits and a recent article by Carr (2003) who considers individual corporate competitive factors. Restricting the subject to typical manufacturing information and automation technology, there are fewer previous references on benefits. White (2003b) discusses these issues further and used an earlier version of the analysis proposed here for evaluating some information technology investments.

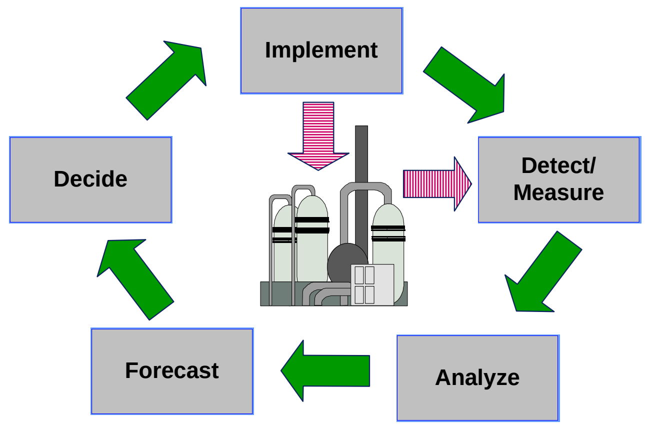
Decision modeling has a long and well populated history as well. The reference by Raiffa (1997) is considered a thorough modern introduction to the overall subject. One significant area of decision modeling in a plant operations environment has concerned abnormal event responses as noted in the survey recently by Venkatasubramanian (2003).

Decision Modeling

There are many types of decisions - negotiations to reach agreement on complex issues among multiple parties, choices on how much to bid for an asset one wants to purchase, etc. In this paper the focus will be on decision modeling in process manufacturing environments.

As discussed in a previous paper (White, 2003a), the typical decision cycle for plant operations, shown below, is a useful model for organizing and categorizing advanced system oriented technologies in the production area.

An opportunity or a problem or a deviation from plan is observed. The first step is to *measure* conditions in the plant or *detect* changes of state to bound the situation and provide base data. At this point there is a preliminary definition of the scope of the problem/ opportunity and most importantly, how much time is available to develop



an answer. Next the data is *analyzed* to obtain the best possible estimate of the current performance of the system (plant) and its history, to potentially spot an anomaly, to identify the uncertainties and to estimate the cost and time requirements for obtaining more information. This further refines the problem/ opportunity statement and the relevant time frames. The outcomes of future alternative action scenarios are forecast. The criteria for *decisions* are developed and a recommended action plan is proposed, including timing. Based on preferences (maybe prejudices) and system constraints, again most particularly time constraints, a plan is actually *implemented*. After this, the cycle repeats. Examples of decisions made in this framework include what products to produce and when to produce them, decisions on the resources required for production including feedstocks and manpower and decisions on when to perform maintenance on a particular item of equipment.

Note that this is not a universal model for all plant decisions. It is not the way decisions are made on who to promote, who should be designated for working a particular shift and a host of other similar questions. It is, however, similar to decision models in other areas where choices must be made to solve an operational problem with time constraints. The popular "six sigma" process has its DMAIC (Define, Measure, Analyze, Improve, Control) steps (Gupta and Wigginhorn, 2003). DMAIC entails defining a problem precisely; measuring to bound and clarify it; analyzing the business process associated with the problem to identify the problem's root cause; improving the process by considering alternative solutions and selecting and implementing the best one; and controlling the process through ongoing measurement to ensure that the problem does not recur. The US Army has its similar OODA Loop (Observe, Orient, Decide, Act) which it uses to understand battlefield issues and evaluate technology, organization and procedures (Boyd in reference Berkowitz, 2003).

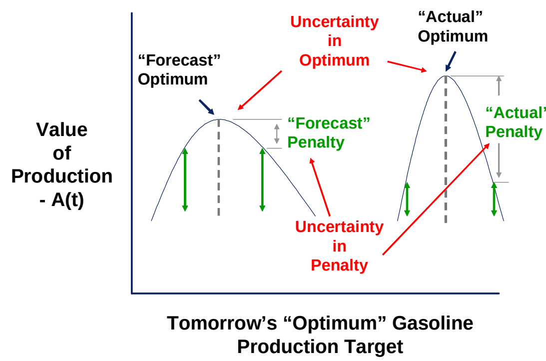
Assessing Economic Value of Manufacturing Facilities

The next step in the analysis is assessing the economic value of manufacturing facilities and the effect of the operations decision cycle on this value. A process plant is an asset and from a financial point of view all assets are valued similarly, i.e. as the net present value (NPV) of the future sequence of after tax cash flows (ATCF) generated, discounted back to the present time with the discount rate chosen to reflect the uncertainty or *riskiness* of the cash flow forecast (Brealey and Myers, 2003).

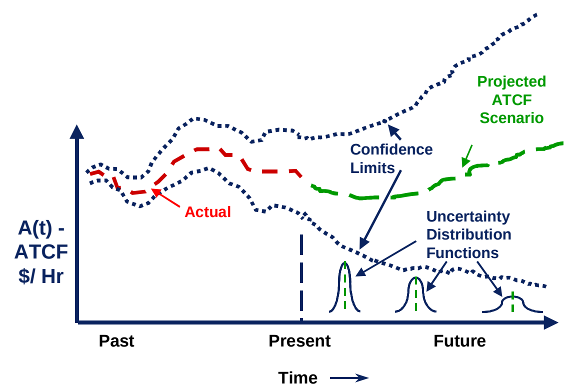
Ultimately the value of any financial investment comes from increased production value at the same costs, or the same production value at lower costs or lower overall invested capital. Information technology doesn't actually do anything directly to create these conditions. It provides us with a better basis for making a decision that will lead to increased value. What is the value of an investment that gives us the option of taking action? How can the value of information that allows us the *possibility* of making a better decision be assessed?

With regard to operational decisions, obviously the future is unknown and actual outcomes from decisions are always uncertain. In the general business environment these uncertainties come from unexpected changes in general economic and market conditions and from competitor actions. For a production plant these effects are observed as unanticipated changes in prices and demands for feedstocks, products and utilities. In addition, there are unscheduled equipment outages, shipping and receipt schedule changes, and many other disturbances. Intuitively, it is recognized that these uncertainties increase as the forecast goes further into the future.

In the figure below, a typical decision scenario for a plant is illustrated. Assume that the "optimum" or "best" operating policy for the plant is forecast for the production of a product, say gasoline, for a time period, i.e. tomorrow, and this generates an expected economic profit. Production amounts plus or minus from this forecast optimum will result in an overall production value less than that of the optimum. If the forecast value of the production is assumed to have a quadratic form with a maximum at the optimum value, its shape is represented as in the figure. If the value curve is relatively flat, there is a small penalty for non-optimum operation, defining the penalty as the loss in value for one unit of production more or less than the optimum. This penalty is sometimes called the marginal value. If the curve is steep, then there is a large penalty. Two types of uncertainty are possible. It may be that the actual optimum, determined by a post period audit, is different than the forecast optimum. In addition it may be that the actual penalty for non-optimum operation is different than the forecast. Both the optimum and the penalty can be modeled as random variables, normally distributed, with a given mean and variance.



The uncertainty in the optimum operating policy can be represented by the lines of constant confidence limits in the figure below. As stated before, it is expected that this uncertainty will increase the further into the future the policy is projected. A similar figure for the uncertainty in the penalty for non-optimum operation can also be derived.



The value of a plant can be taken in standard financial terms as the expected present discounted value of the forecast after tax cash flow – A(t) – over the time from the present forward where the forecast is derived from the decision cycle.

This can be expressed mathematically as:

$$V = E(A(t)) = \left[E\left(\int_0^{\infty} A(t)e^{-rt}\, dt\right) \right]$$

where A(t) is a random variable typically modeled as an Ito process and r is the appropriate discount rate (Dixit and Pindyck, 1994). The question now becomes – "What is the appropriate discount rate?"

An example may make the answer clearer. Suppose there is the chance of buying a US Treasury bond for $100 that will almost surely return $105 in one year. There also is the alternative choice of buying a stock that is projected to be worth $105 in one year but it could be worth more or it could be worth less. The uncertainty in the value of the stock can be characterized by saying that the expected value in one year is $105 with a standard deviation of 12% (typical for an individual stock). A rational investor would always pay less for the stock than the bond. Indeed in the standard financial analysis known as the Capital Asset Pricing Model (CAPM) (Luenberger, 1998), the amount you should be willing to pay (assuming the stock has a covariance of 1 with the target investment portfolio) is:

Price = Expected Value Of Asset At End Of Period/ (1 + Risk Free Discount Rate For Period + k * Standard Deviation Of Expected Value)

P = ($105)/(1+ 0.05 + k (0.12)) = $95.62; for k = 0.4 (a typical value)

Where k = market price of risk, i.e. the amount by which the return of the stock must increase over the risk free bond to compensate for the risk.

The appropriate discount rate to use for evaluation of an investment is the risk free rate plus an adjustment factor which is a function of the variability in the forecast of the expected cash flow. In other words, risky assets are worth less than stable assets of the same expected value, which confirms our intuitive bias, and the reduction in value is a function of the standard deviation of the forecast. Equivalently, at the same projected mean value of cash flow, a plant with an almost certain results is worth more than a plant with uncertain ones.

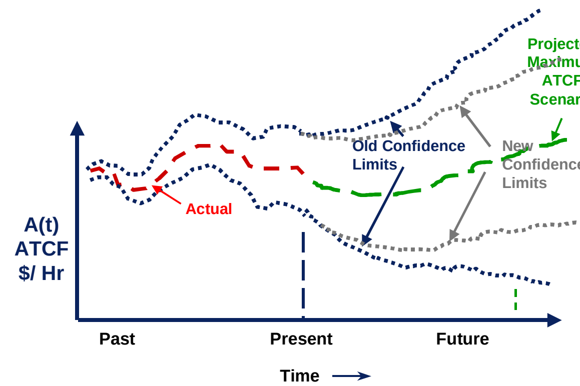
By analogy the appropriate discount rate for the future value of the effect of a decision depends on its uncertainty measured as the standard deviation of the forecast with a high value justified when the uncertainty is high and a lower one when the uncertainty is less. This leads to the central proposition of this paper.

Investments in system technologies can generate value by reducing future uncertainty in the projected cash flows and the economic reflection of this effect is to reduce the required discount rate and hence to increase the expected value of the decisions made with the information.

Consider the discrete equivalent of the integral above for the limiting case where the ATCF is forecast at a constant $A per year, and the discount rate is r (r less than 1). Then the value V of the asset is given by the formula below. As r gets smaller, the value increases.

$$V = \sum_{n=1}^{n=\infty} \frac{A}{(1+r)^n} = \frac{A}{r}$$

This is illustrated graphically in the figure following where it can be seen that the technology can have the effect of reducing the standard deviation of the forecast going forward.



With reduced uncertainty, that is tighter confidence limits, the discount rate is reduced and the expected value increased.

Note that there can be additional sources of benefits for these technologies. They may reduce production costs by reducing staff or other resource requirements for normal plant activities and these benefits would be additive to those considered here.

System Technology Effects on Economics

How can new system technologies improve the forecast accuracy? Reviewing the decision cycle again, the forecast will be improved by better measurement of the current state of the system, by reducing the delays in the loop including earlier detection of disturbances, by modeling better the plant responses and expected disturbances, by increasing the number of alternative forecast scenarios considered and the rigor of their evaluation. These are precisely the areas that system technologies affect most.

Some corollaries:

This approach to analysis of value leads to some associated propositions.

The greater the uncertainty in the business and production environment, the greater the potential benefits from the system technology.

If there is no flexibility in operation, i.e. the plant production is fixed and no set of alternative actions is possible, then the system technology investment has little or no value in the context of this analysis. Similarly if the system technology does not affect the decisions that have the most economic impact, its economic return will be diminished.

If the optimum for production is flat, which means that there is not much difference in economic value with different production levels then the value of improved information is also less.

The principle of diminishing returns applies to system technology investments just like everything else. The highest valued investments will be those with the highest uncertainty adjusted marginal value. Improving forecast accuracy from 50% to 90% will be more valuable than improving it from 90% to 99%. There is a limit to the improvement in the accuracy of a decision that will be realized from improved information due to the inherent uncertainty of outside events.

Example

As an example consider a 100,000 BPD refinery. Assume an after tax cash flow - ATCF - (after tax net income plus depreciation) of $2/ Bbl (the US average for 2001). For simplicity in this example, assume the projected cash flow is constant for future periods. Further assume the base case one year forecast standard deviation is 20%. This leads to a base case discount rate for evaluation of cash flows from the refinery of 13 % (0.05+0.4*0.2=0.13).

Consider the case of an investment in a new real time historian database for the refinery. The software will provide a platform to collect actual vs planned performance for the plant, provide a collection point for information about current operation and demands, and provide an enabling platform for other applications. If it is assumed that the software will reduce the one year forecast standard deviation by 1%, with no change in the standard deviation thereafter the benefits are:

$$(1/(1+.12) - 1/(1+.13))*100000*\$2*360 \text{ (days operation/ year)} = \$568,900 \text{ per year.}$$

Other assumptions can be similarly evaluated.

Conclusions

In this paper a new method is proposed for estimating the value of system technology investments based upon their effect on the projected uncertainty of forecast cash flows from the plant. It might be argued that this approach replaces one difficult to quantify problem with another. Clearly the investment benefit analysis procedure discussed here requires more effort than simple "rules of thumb" and also requires increased data about the sources of business value, about which decisions have the most economic impact and the uncertainties in forecasts. However, the methodology focuses attention on how the system technology will be used and the possibilities for it to affect the business and economic decisions made in the plant. The result is an analysis grounded much more strongly in business value and one with a clearer source of the benefits.

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