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PUTTING NUMBERS ON INTANGIBLE BENEFITS

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Abstract

Intangible benefits have been a thorn in the side of information technology project valuation efforts. These benefits are often comparable to tangible benefits in magnitude, and so should not be ignored. Yet, unless we can attach numbers to them, it is difficult to combine them in a consistent way with tangible benefits to reduce the chances of underestimating the true value of a project. The lack of agreement in both theory and practice on how to treat intangible benefits suggests that it continues to be an unresolved yet important issue. In this paper, we suggest a disciplined way, based on system dynamics, to quantify so-called intangible benefits. Although it is not algorithmic, the method still has substantial structure and can be implemented and estimated to varying degrees of detail to suit project needs. The method is demonstrated by applying it to a cellular service provider context. A simple but key notion that is used to develop our approach is that of induced observability. It helps to operationalize intangible benefits in a way that facilitates quantification for purposes of project valuation.

Keywords: Intangible benefits, IT project valuation, system dynamics

Introduction

You are a member of the IT steering committee of a cellular services company that has managed to attract new customers and survive financially in a very competitive market. However, in recent times, there have been increasing complaints about its customer service, putting it at competitive risk. As part of the effort to address the situation, a project has been proposed, that involves significantly improving functionality and capacity of the existing Web-based system that is used for customer support. Accompanying the proposal is a long and carefully itemized list of different cost items with numbers for most items. The list of benefits is also lengthy. However, only some come with numbers. Several others—such as improved customer satisfaction and enhanced reputation—have lengthy narratives but no numbers. You look at the estimated return on investment in the proposal and wonder how to factor in the benefits in this second category when making your recommendation. If you ignore them for lack of numbers, the project looks less attractive, and you worry that you could end up recommending against a perfectly worthy project. So you reread the narratives and, based on some combination of intuition, knowledge, experience and logic, you informally generate your own mental estimate of these benefits and this leads to your voting in favor of the project. Now you worry that you may have overestimated the benefits and accepted a project that should not have passed muster.

As more and more organizations insist on formal evaluation processes for selecting IT projects, scenarios such as this are being played out in numerous organizations on a regular basis. Intangible benefits have continued to be a thorn in the side of the evaluation process for some time now (Keen and Digrius 2003; Spokes 1993). Everyone knows these benefits are important and

should be included in the analysis—but how? There is no single widely agreed upon method for handling intangibles. There is a lot of hand wringing about this deficiency (Hoffmann 2003), but the pressure to engage in formal assessment of IT projects remains undiminished in practice. If anything, this pressure has only increased with time. It is evident that the treatment of intangible benefits in IT project valuation continues to be an important and relevant problem and one that could benefit from further inquiry (Noyes 2002). The objective of this paper, therefore, is to inquire if, and how, intangible benefits might be quantified in a manner that would be useful for IT project valuation.

For completeness, we should note that there is extensive research literature on valuation of IT investments, but most of this literature is at the firm or country level of analysis (see, for example, Dewan et al. 1998; Kraemer et al. 1992). While their findings are useful in informing policy at the firm or national level, they are not directly usable for assessing an individual project. The level of aggregation in the analysis is too high to accommodate characteristics of individual projects that are relevant to their assessment. The academic literature on methods for justifying IT projects is somewhat sparse (Sarkis and Sundarraj 2001). Real options theory has been suggested as one approach (Kim and Sanders 2002). The analogy is that when one invests in an IT project, it is like buying an option on improved performance. As with financial options, the uncertain future event—improved performance—may not come to pass. Thus, methods for valuing financial options ought to be applicable in assessing IT projects. Net present value approaches are still widely used in practice (CIO 2003). The practitioner literature also documents other approaches to valuing an IT project (Mayor 2002). These include traditional return on investment type financial calculations and balanced scorecard approaches that attempt to combine financial and nonfinancial criteria. No one approach to justifying IT projects dominates all others. However, note that practically all of the established methods depend on having numbers for their costs and benefits. In particular, this means having numbers for benefits, and this should include numbers for intangible benefits. There is no good way to factor intangible benefits into a project assessment unless we can come up with some number for them, however approximate that may be.

In view of this existing theoretical and practitioner literature on IT project valuation methods, it is important to emphasize that the scope of our present inquiry does not extend to the full project valuation process. It focuses on the treatment of intangible benefits only. However, the outcome of our investigation would be applicable to any valuation approach, be it financial ROI, real options pricing, balanced scorecard, payback period, etc. This is because, even though they differ in their assessment procedures, each of these approaches needs numbers for benefits as inputs. The next section makes some observations about intangible benefits and how they manifest themselves in project value. The third section reviews the methodology to be used; this methodology is then applied to the cellular services customer support project to develop a model to quantify the intangible benefit. Following a report on experiments with the model, we conclude with a discussion of the shortcomings of this approach and some caveats concerning its proper use.

The Nature of Intangible Benefits

At first glance, any attempt to quantify intangible benefits seems a contradiction in terms. After all, Webster's dictionary defines *intangible* as: "1. that cannot be touched; incorporeal; impalpable 2. that represents value but has no material being." The very definition of intangible seems based on an inability to quantify and measure the entity. Fortunately, the definition itself suggests a way out of the quandary. Note that the problem arises from the second part of the definition—i.e., *cannot be touched* or *no material being*. However, notice also the recognition that intangibles represent value. With respect to the hypothetical scenario presented in the introduction, customer satisfaction, by itself, has no material being. The reason for including it as a benefit is a belief, on the part of whoever proposed the project, that it represents value. In fact, the narratives that accompany intangible benefits in IT project proposals are attempts to justify this belief based on some informal common sense reasoning. This observation leads us to introduce a simple notion which we term *induced observability*. It holds that even though intangible benefits have no material existence, they must induce observable outcomes that are deemed desirable. The operative words are *induce* and *observable*. Observable implies detection, and hence, being amenable to a determination of magnitude. Induce implies causation—i.e., one must lead to the other via some identifiable mechanism. If it does not induce any observable outcome, there is no way to tell if the value associated with an intangible benefit has been realized. Hence, its inclusion in the project evaluation process is moot. Note, however, that the term *induced* allows for indirect effects. In other words, there may be several intermediate causal effects on the path from intangible benefit to observable outcome. Therefore, if it is possible to represent this chain of effects from intangible benefit to observable outcome in a computationally tractable manner, we have a basis for putting numbers on these benefits in a way that is relevant for purposes of project evaluation. In the next section, we describe a methodology that allows us to do so.

Methodology

The methodology we choose to use for modeling the induced observable outcomes of intangible benefits is system dynamics (SD) (Coyle 1998; Richardson 1996). We provide a brief overview here, since the methodology has not been commonly used in the Information Systems literature. Further technical details may be found in the references just cited. Simply stated, SD is a mathematical language to represent the causal structure of a system. The domains from which systems are drawn can be extremely varied. Among others, they may be physical (e.g., rainfall patterns), economic (e.g., price controls), or managerial (e.g., strategy formulation). The distinctiveness of SD is that it links causal structure to system behavior in computational form. Consider the very basic business operation of replenishing inventory. As sales occur, inventory falls. Periodically, orders are placed to restore inventory to a desired target level. These orders are fulfilled, after some delay, by shipments from warehouses. This is the well-known “order-up-to” replenishment policy. The causal structure of this “system” is represented in three different, but equivalent, forms. The first, called a causal loop diagram (CLD), is shown in Figure 1. Links show cause-effect relationships and their polarities show the direction of effect. A positive polarity means that the direction of change in the effect is the same as the direction of change in the cause. (In particular, it does *not* mean that the effect only increases in magnitude.) If the cause decreases (increases) in magnitude, the effect decreases (increases) in magnitude. A negative polarity means the direction of change in the effect is the opposite of the direction of change in the cause. (In particular, it does *not* mean that the effect only decreases in magnitude.) This causal structure can now be used to deduce the behavior of this system. By following the polarities of the links around the loop, it can be easily seen that if current inventory level decreases, inventory shortfall increases, production increases, leading to an increase in current inventory. In other words, a drop in inventory induces an outcome that ultimately corrected the drop. This is a classical negative feedback loop. Figure 1 can be translated to the second representation, called a stock-flow model, as shown in Figure 2.

Figure 2 has exactly the same variables as Figure 1, but shows new symbols—a box and pipes with regulators on them. The former represents stock variables—i.e., accumulations of things. The latter represent flows—i.e., rates of change of things. These rates are controlled by information flows, represented by the thin directed arrows in the figure. For instance, inventory shortfall is the information that drives the flow called *Production*. Variables such as *inventory shortfall* and *desired inventory level*, are called *auxiliaries*. They represent data constants or formulas that compute a derived value. The stock flow model of Figure 2 is only a visual form of the collection of equations shown in Figure 3.

Note that equation 2 in Figure 3 is the discrete-time version of a differential equation describing how inventory changes over time. The causal relationships among the variables of Figure 1 are represented by this equation and the remaining ones in Figure 3. Therefore, the collection of equations in Figure 3 can be simulated to generate the behavior of the replenishment system in response to sales. As a demonstration, we show in Figure 4 the response of this system to a step increase in sales. Inventory level exhibits the well-known bullwhip effect in inventory management, confirming that the model of Figure 3 is a reasonable representation of reality for this inventory problem. Therefore, the SD methodology is well suited for the problem being addressed in this paper, since it allows us to represent the induced observable outcomes of intangible benefits in a computational form.

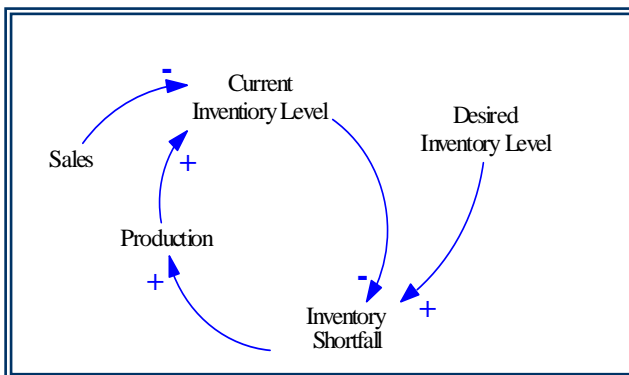


Figure 1. CLD of Replenishment

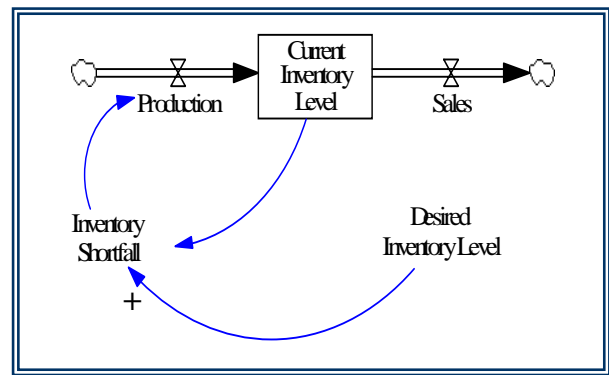


Figure 2. Stock-Flow Model of Replenishment

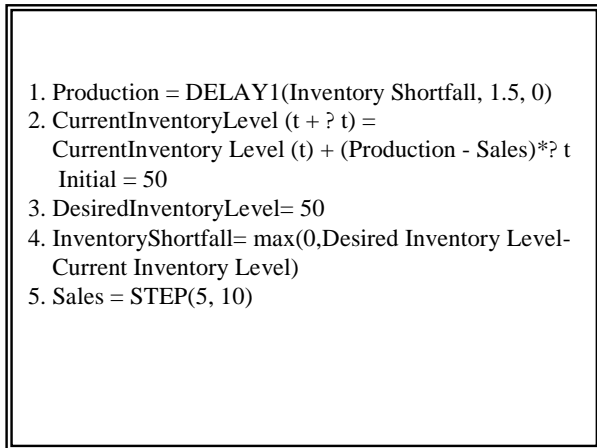


Figure 3. Mathematical Representation of Inventory Replenishment System

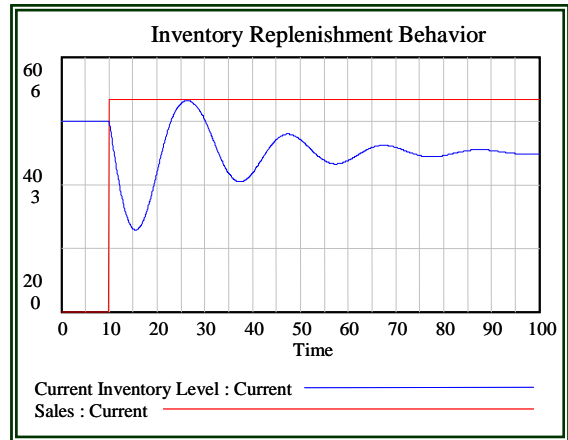
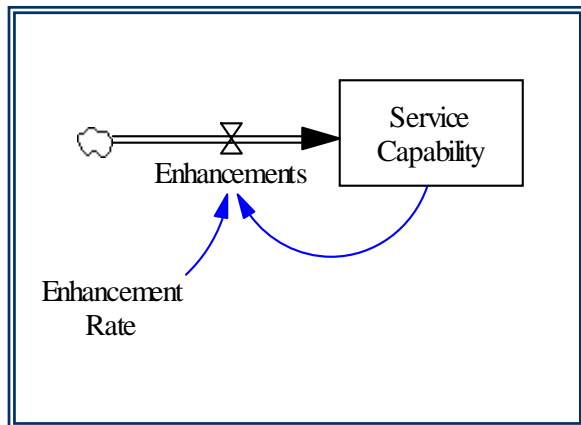


Figure 4. Induced Behavior of Replenishment System

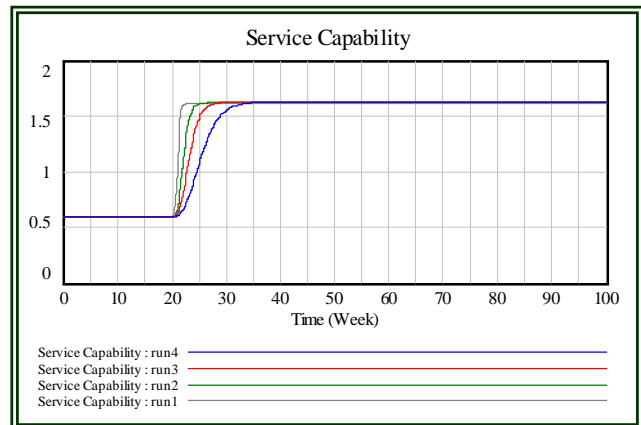
Using SD to Represent Intangibles

To demonstrate how SD can be used to put a number on intangible benefits, we apply it to the scenario described at the beginning of this paper. In the scenario, the proposed project is to enhance an existing customer support Website, and one of the claimed intangible benefits is improved customer satisfaction. How can one put a number on this intangible benefit in order to factor it into the project assessment in a consistent manner with tangible benefits? Using the notion of induced observability introduced earlier, the first step is to identify observable outcomes of this benefit, and then uncover how the former is induced by the latter. This causal structure will then be represented using the formalisms of SD, which will then allow us to quantify the benefit for purposes of assessing the project.

In the context of the cellular company, a major observable outcome of improved satisfaction should be reduced turnover. There is ample evidence in the practitioner literature to confirm that customer service is strongly correlated with customer retention (O’Shea 1996). Moreover, with the new wireless number portability in effect, the top 10 predictions for 2004 include a shift in focus from price to quality and customer service (Tele-Service News 2004). We now proceed to describe how this observable outcome is induced by improved satisfaction, and simultaneously build the resulting causal structure using stock-flow modeling described earlier.



(a)



(b)

Figure 5. Stock-Flow Model of Project Implementation

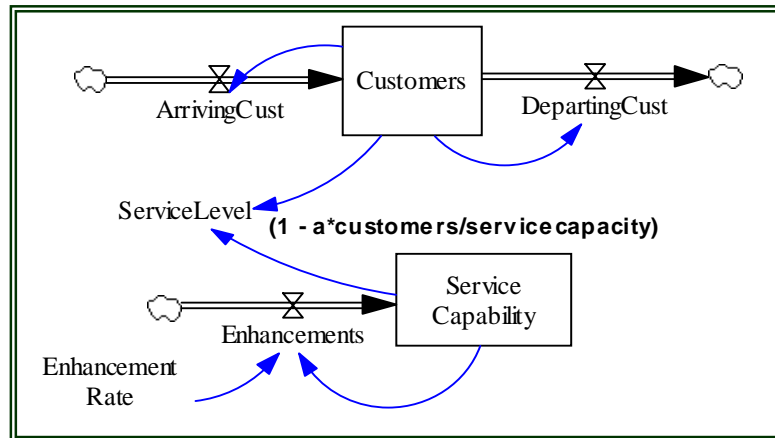


Figure 6. Simple Causal Structure for Service Level

The most direct effect of implementing the system enhancement is not an increase in satisfaction, but rather an increase in the organization's capacity to service customers. This direct cause-effect relationship is modeled in Figure 5a. The capacity of the organization to service customers is clearly a stock variable. The proposed project will enhance that capability and is shown as a flow into the stock in Figure 5a. Using *EnhancementRate* as a parameter, one can represent, albeit coarsely, more or less aggressive implementation plans. When *EnhancementRate* is one, the entire project is implemented instantaneously—hardly realistic, but a scenario that can serve as an extreme point for analysis. With lower rates, the package is implemented more slowly and service capacity increases gradually to its final level. This variation is shown in Figure 5b.

The increase in service capacity will induce an improvement in service quality. Figure 6 expands the structure of Figure 5a to include this effect. It is well known from the operations literature (Fitzsimmons and Fitzsimmons 1994) that service quality is a nonlinear function of both capacity and load, as shown by the formula for service quality in Figure 6. As a first approximation, the customer population is assumed to be homogeneous. So load is determined by the number of customers and an average load that each places on the system, the latter represented by the coefficient *a* in the formula. In Figure 6, notice that the stock of *Customers* may increase or decrease, depending on arrival and departure rates. We must capture, however coarsely, the reality that the number of *Customers* can change. After all, if the number of customers remained fixed, there would be little need to implement the project. For the moment, the information that drives arrival and departure rates will remain unspecified. It is the experience with service levels that induces customer satisfaction. Sustained high service levels generate higher levels of satisfaction, and vice versa. Figure 7 shows the structure of Figure 6 extended to capture this causal effect.

Note that *Satisfaction*, although an intangible, can be represented as a stock since, like goodwill, it accumulates or decays over time. Following the discussion in the preceding paragraph, the variable *ServiceLevel* drives *ChangeInSatisfaction*. This is modeled in Figure 7 by an arrow from the former to the latter. However, to have a computational model, we also need to specify a functional form for this relationship. Two aspects of this relationship are known from the literature (Lilien et al. 1992): (1) an increase in service level results in an increase in satisfaction, and vice versa (2) there are saturation effects—satisfaction will not increase or decrease indefinitely. A commonly used functional form that meets these characteristics is the hyperbolic tangent. So we express the relationship as follows:

$$\Delta Satisfaction / Satisfaction = a * Tanh(b * \Delta ServiceLevel / ServiceLevel).$$

By varying the coefficients *a* and *b*, one can control the amplitude and gradient, respectively, of the relationship. Figure 8 shows variations in gradient with amplitude remaining fixed.

Note that the *x* and *y* axes of Figure 8, being fractional changes, are dimensionless. This is designed deliberately in view of the lack of standardized units for measuring customer satisfaction or service. Surveys often rate these variables using point scales, such as the J. D. Power Satisfaction ratings, but they are not standardized units like feet, pounds, or gallons. Therefore, by using fractional changes, we have a computational way of driving *Satisfaction* using *ServiceLevel* in a way that captures known patterns of the effect. Moreover, by using dimensionless fractional changes to drive the flow, the variable *Satisfaction* in Figure 7 can remain in the point scale form commonly used in practice.

Changes in *Satisfaction* will, in turn, induce behavior in existing customers. Specifically, if *Satisfaction* falls below *SatisfactionThreshold*, customers start to leave. In practice, the larger the shortfall, the higher the fraction of existing customers that depart, subject to saturation effects. For notational convenience, let us use “%x” to denote the fractional change ($\Delta x/x$) expressed as a percentage. A simple functional form that meets these characteristics is

$$\Delta \text{DepartingCustomerRate} = a * (1 - \exp(-b * \% \text{Shortfall})) \text{ if } \text{Shortfall} > 0, 0 \text{ otherwise}$$

where $\text{Shortfall} = \text{SatisfactionThreshold} - \text{Satisfaction}$. The parameters *a* and *b* can be used to control the amplitude and gradient of the relationship. As before, note that the independent and dependent variables in this formula are both dimensionless. Therefore, even though we do not have standardized units to measure satisfaction, as long as *Satisfaction* and *SatisfactionThreshold* are represented using the same point scale, we can capture their causal effect with some consistency using the formula above. To complete the structure we need to represent the causal relationship that drives arriving customers. This is very similar to the one described for departing customers, with one difference. Arrival of new customers is driven by *Reputation* rather than service level, since they have not experienced actual service yet. And reputation is built up over time based on satisfied current customers spreading the word through a variety of mechanisms. Hence, reputation building is a long-term process. When *Reputation* exceeds *ReputationThreshold*, the latter being the reputation of a benchmark competitor perhaps, new customers start joining at a rate determined by this differential. The functional form of this relationship is the same as that specified above for departing customers, and uses the dimensionless form of the independent and dependent variables. This completed causal structure relating the intangible benefit customer satisfaction to the observable outcome turnover can be seen in Figure 7. The ultimate observable outcome of interest, *Turnover*, can now be easily expressed as *DepartingCust/Customers*. There are studies in the practitioner literature that report how much it costs to attract a new customer relative to the operating margin generated by an existing customer (e.g., Bucholtz 1998; Pierce 2001). Thus the number for turnover can be translated to a monetary estimate for use in assessing the project.

Clearly, some of the variables in Figure 7 are affected by other parameters as well. For instance, while *ArrivingCust* is indeed driven by *Reputation* as shown above, price is at least as important a driver of that variable, if not more. The same can be said for *DepartingCust*. Moreover, there are other observable outcomes, besides *Turnover*, resulting from customer satisfaction. The intent of developing the model of Figure 7 is not to capture all intangible benefits and observable outcomes for the proposed project. Rather, it is meant to be a proof-of-concept model, showing how the SD methodology can be applied to link intangible benefits to observable outcomes. The model in Figure 7 is based on a few causal relationships each of which has very simple functional form. These functional forms are consistent with the behavior of these relationships as observed in practice. Therefore, there is reason to infer that the turnover behavior generated by this model is a usable approximation of the real behavior of this observable outcome. In the next section, we demonstrate how the model can be applied to get useful results to support the quantification of the intangible benefit noted here.

Using the Model

Since the functional forms of the causal relationships have been fully specified in the previous section, Figure 7 can be translated to its equivalent collection of differential equations using standard definitions of stocks and flows in SD (compare Figures 2 and 3 to review this mapping). The experiments reported in this section were conducted by simulating this collection of equations. The time unit for the runs is weeks, and the simulation period is 128 weeks (about two and a half years). This is long enough to detect any delayed effects of the intangible benefits. The project is assumed to start at $T = 0$, and the implementation duration is 16 weeks. Unless noted otherwise, the coefficients *a* and *b* for the different functional relationships are set to 0.2 and 0.5, respectively. When completed, the technical enhancements implemented by the project are assumed to result in a 20 percent increase in service capacity. *SatisfactionThreshold* and *ReputationThreshold* are both set at 0.8 (on a scale of 0 to 1) as would befit a competitive industry like cellular services. The scenario described in the introduction talks about a viable ongoing cellular services company that has managed to attract new customers but which is now experiencing complaints about customer service. Therefore, the initial value of *Satisfaction* is set to 0.7—i.e., lower than *SatisfactionThreshold*—to reflect the scenario described here. Similarly, the initial value of *Reputation* is set to 0.85—i.e., just slightly above *ReputationThreshold*—to reflect the fact that the company has been able to attract customers. Figure 9a shows the behavior of *Customers*, while Figure 9b shows that of *Turnover*, resulting from running the model with these baseline parameter settings.

The qualitative characteristics of the runs are consistent with what one would expect from the project. Figure 9a tells us that while the project is being implemented (it takes 16 weeks to do so in the simulation), the number of *Customers* drops since there are disgruntled customers who are leaving. However, once the project is implemented (i.e., after about $T = 16$ in Figure 9a), the number of *Customers* starts to rise once again, reaching an equilibrium value after about 50 weeks. This is because the project has resulted in higher service capacity which, as per the model of Figure 7, leads to higher service level and higher satisfaction,

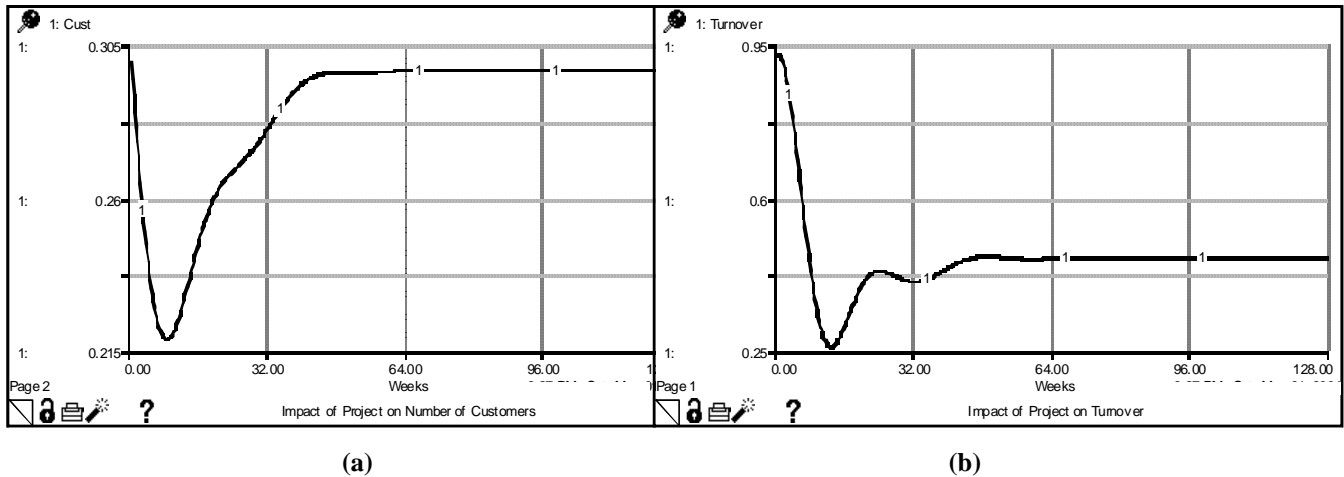


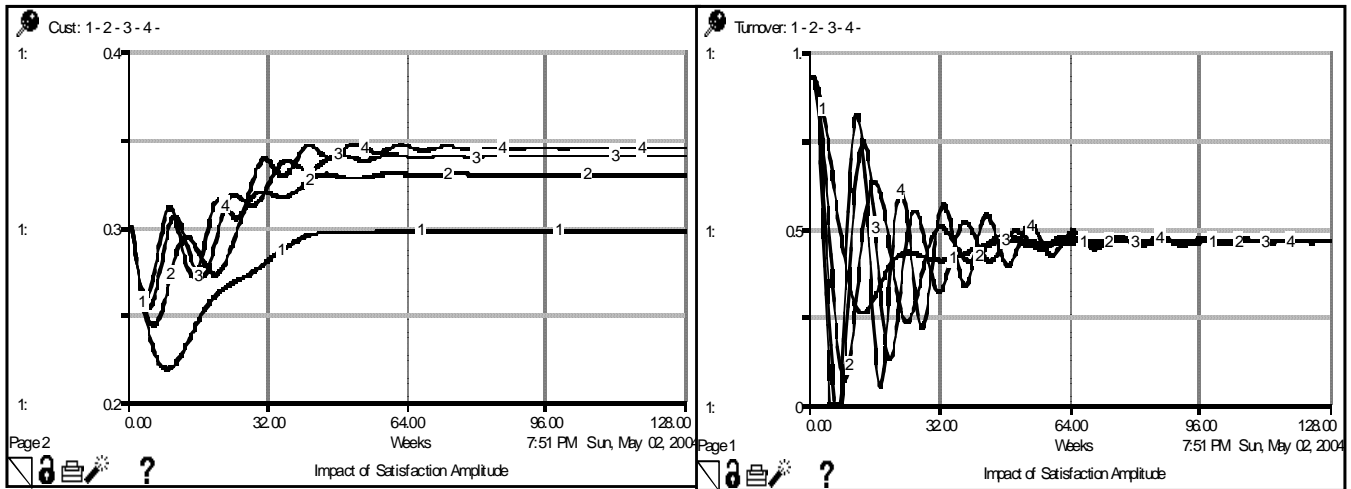
Figure 9. Impact of Project on Observable Outcomes: Baseline Run

which in turn reduces the departure rate of customers. Also, as satisfaction increases, this leads, after some delay, to an increase in new customer arrivals as per the causal effects in Figure 7. These two effects together lead to an increase in *Customers*. Figure 9b shows that even though *Turnover* oscillated a little, it continues to drop from its initial value of about 0.92 and, not long after the project implementation is completed at $T=16$, reaches a steady state value of about 0.46. Taken together, the two graphs allow us to make the following, very preliminary, but quantitative statement. As a result of undertaking the project, a service capacity increase of 20 percent will likely result in the number of customers staying about the same, but turnover will be reduced by about 50 percent (from 0.92 to 0.46). One can now attach monetary figures to this estimate based on industry cost numbers of the kind mentioned earlier in this paper. Of course, one simulation run is simply not sufficient to lend confidence to an assessment such as that given above—hence the qualifier. Nevertheless, the baseline run does demonstrate the capability of the SD approach to attach numbers to intangible benefits in a way that is directly relevant for IT project evaluation. To bolster the preliminary assessment and arrive at a quantitative estimate in which we have more confidence, it is necessary to perform variations of the baseline run to account for imprecision in the parameters driving the model. This sort of sensitivity analysis is standard practice in the use of SD models for decision making (Coyle 1998). In each of the following simulation runs, only the parameter that is varied is noted. The others remain as mentioned in the baseline run above.

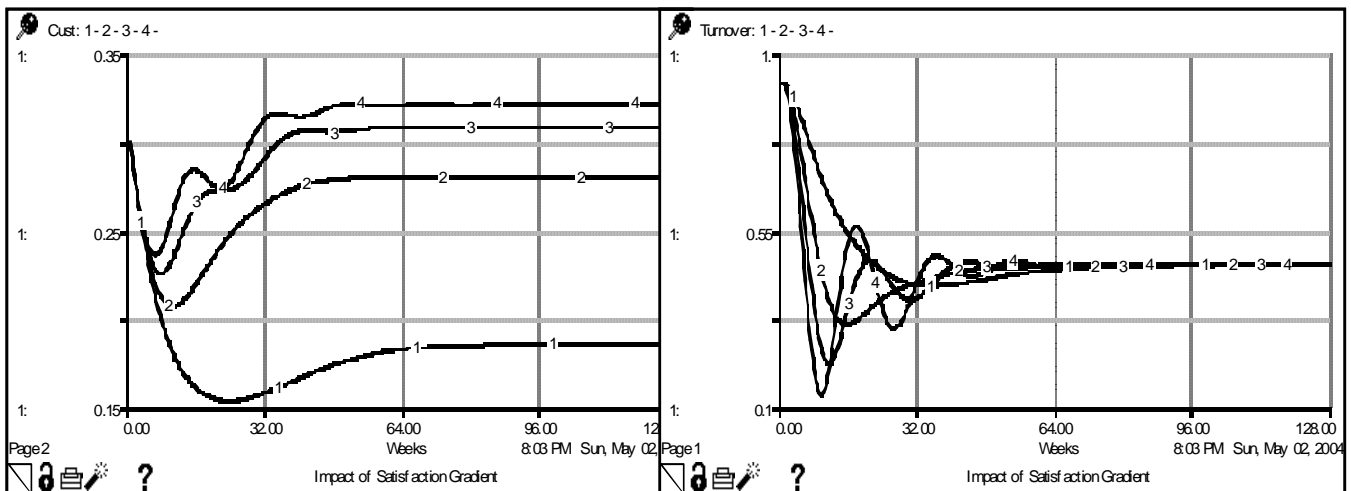
Sensitivity to Satisfaction Coefficients

Recall that the relationship between *ServiceLevel* and *Satisfaction* was captured using a hyperbolic tangent function with two coefficients, **a** and **b**, that control the amplitude and gradient of the function, respectively. They range between $[0,1]$ and their physical interpretation is as follows. The gradient **b** controls the sensitivity of customer satisfaction to changes in service level. This gradient reflects general customer attitudes toward service levels. Over time, customers have come to expect higher levels of service. Hence, small deviations in service levels are likely to result in large swings in satisfaction, implying a higher value of **b**. It is unlikely that **b** would vary over a wide range in the current business environment. The amplitude **a** reflects the maximum swing in satisfaction that could result from a change in service level. Figures 10a and 10b show the sensitivity of *Customers* and *Turnover* to the amplitude, while Figures 11a and 11b show sensitivity to the gradient of this functional relation for satisfaction. The results suggest that even a four-fold increase in the satisfaction amplitude (Figure 10b) results in no change in the equilibrium value of turnover. In all four runs, turnover dropped from about 0.9 to just under 0.5 percent. However, the equilibrium value of customers changed from 0.3 to about 0.35 (Figure 10a)—an increase of about 16 percent. Thus we can conclude that our baseline results are not particularly sensitive to imprecision in knowing the amplitude **a** of this functional relationship.

The finding that the two observable outcomes are not very sensitive to satisfaction amplitude is not altogether unexpected. After all, even if the maximum satisfaction/dissatisfaction level were to increase, the action that one can take as a result remains the same: one can stay or leave. You cannot leave twice if the maximum dissatisfaction level is twice as high. Unlike the case for amplitude, however, Figures 11a and 11b show that the observable outcomes are indeed sensitive to the gradient **b** of the satisfaction relationship. While the equilibrium turnover level does not change with **b**, the equilibrium number of customers does. In fact, as Figure 11a shows, a four-fold change in the gradient **b**—from 0.2 to 0.8—results in the equilibrium value of customers



(a) (b)
Figure 10. Sensitivity to Satisfaction Amplitude: a = 0.2, 0.4, 0.6, 0.8



(a) (b)
Figure 11. Sensitivity to Satisfaction Gradient: b = 0.2, 0.4, 0.6, 0.8

changing from about 0.18 (run # 1) to about 0.33, or close to a 100 percent increase. This equilibrium value exhibits diminishing returns; notice that runs 3 and 4 in Figure 11a are closer together than runs 1 and 2, even though the four runs are for equally spaced values of **b**. In other words, the equilibrium value of *Customers* does not change very much for high values of **b**. This is fortunate since for a competitive industry like cellular services, the value of this gradient is indeed high. Therefore, the baseline results for *Turnover* and *customers* shown earlier should be reasonably realistic, even though we do not know the exact values of **a** and **b** for the functional relationship between *ServiceLevel* and *Satisfaction*.

Sensitivity to Departure Rate Parameters

In the causal model of Figure 7, the intangible variable *Satisfaction*, drives the outflow of departing customers—*DepartingCust*. The functional relationship between the two variables is given by the formula:

$$\Delta \text{DepartingCustomerRate} = a * (1 - \exp(-b * \% \text{ Shortfall})) \text{ if } \% \text{ Shortfall} > 0, 0 \text{ otherwise}$$

In this section, we examine the sensitivity of the two observable outcomes *turnover* and *customers*, to variations in the amplitude **a** and the gradient **b** of this relationship. The physical interpretation of these two coefficients is as follows. Both coefficients vary between [0,1]. A high value of **b** implies that a small fractional change in satisfaction will result in a comparatively larger fractional change in departure rates. This is the case when the cost to switch between alternatives is relatively painless. Until recently, one of the biggest barriers to customers switching cellular providers was the fact that the customer’s telephone number would need to change. Now, with local number portability, that barrier has been removed. Nevertheless, the switching costs are not zero. Sometimes, subscribers have to get a new telephone handset even if the phone number stays the same. Then, all the information from the first handset has to be transferred to the new handset by a process that is still quite cumbersome. Nevertheless, it would be fair to say that in the current cellular services market, customers are finding it increasingly easy to switch, implying a relatively higher value of **b**.

The amplitude of this relationship, **a**, is the value of the fractional change in departure rate as the independent variable *Shortfall* tends to a high extreme. At this point, most all existing customers are considering a switch. Therefore, **a** would likely be determined by the aggregate capacity of the remaining providers to absorb defecting customers. For example, customers who have to travel frequently outside the United States often subscribe to GSM cellular services within the United States, since this is the cellular standard across most of the world, and they can then use their mobile phones seamlessly across the world. However, the number of GSM service providers within the United States is still very low. Therefore, if customers are dissatisfied with their GSM service provider, they may all want to change, but the maximum rate at which this could happen would be limited due to the few alternate providers available to absorb this defection.

Figures 12 a and 12b show the sensitivity of the two observable outcomes to the amplitude **a**. The steady state value of *Turnover* is not particularly sensitive to this parameter. Except for the first run, turnover stabilizes at about 0.5 percent for the remaining three. The steady state value of *Customer* exhibits greater variability as a function of **a** than did *turnover*. Nevertheless, notice that runs 3 and 4 are closer together than runs 1 and 2 in Figure 12a. Hence, we can see that the variability is lower for values of **a** that are closer to 1. Figures 13a and 13b show the sensitivity of the two observables to variations in the gradient **b**. Once again, the pattern is similar to that for the amplitude **a**. In other words, the steady state value of *Customers* shows greater sensitivity to changes in the gradient “b” than does the steady state value of *turnover*. Furthermore, the sensitivity is lower for values of **b** that are closer to the maximum value 1.

Given the characteristics of the cellular services market, which would call for higher values of **a** and **b**, the implication of Figures 12 a and 12b for purposes of project valuation is that the baseline runs shown at the start of this section are probably not too far off the mark with respect to the functional relationship between satisfaction and departure rate of customers. Sensitivity tests were performed on the functional relationship for reputation and customer arrivals with similar findings.

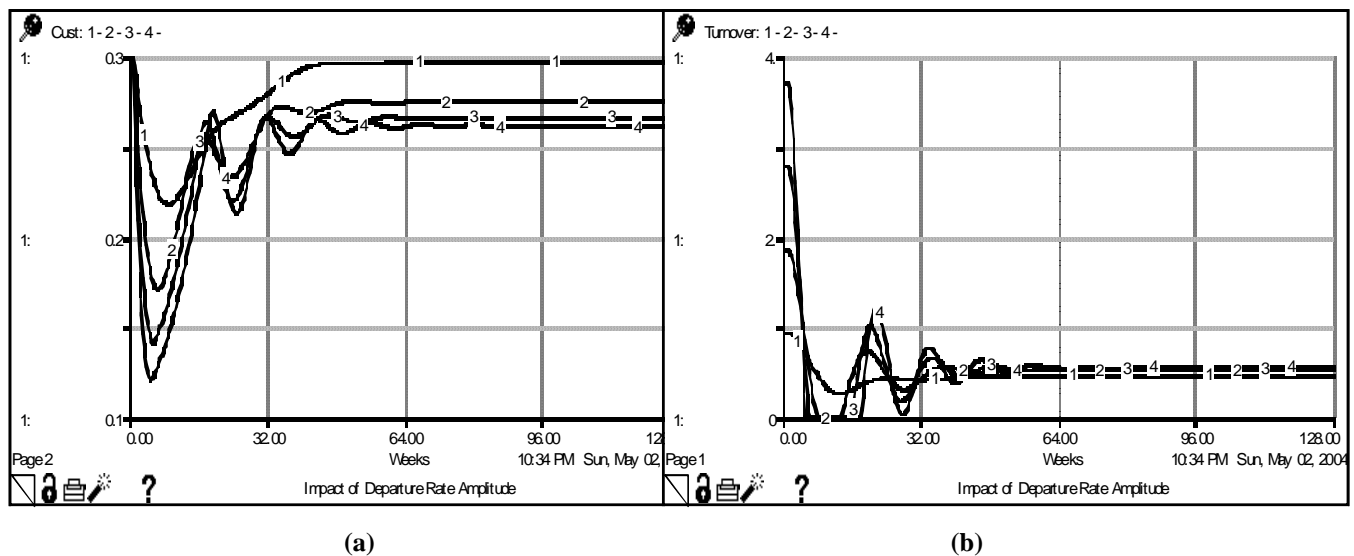


Figure 12. Sensitivity to Departure Rate Amplitude: a = 0.2, 0.4, 0.6, 0.8

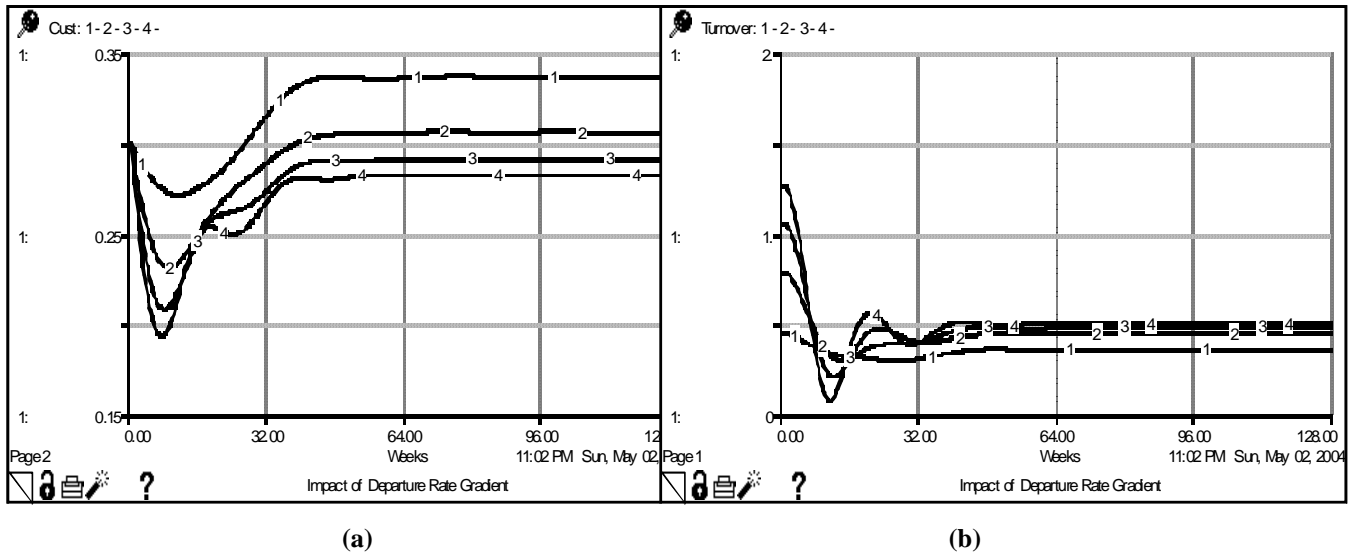


Figure 13. Sensitivity to Departure Rate Gradient: $b = 0.2, 0.4, 0.6, 0.8$

In summary, baseline runs such as that reported at the beginning of the section, must always be complemented by extensive sensitivity testing with relevant parameters of the SD model. Since the causal model links intangibles to observed behavior, it is more than likely that coefficients of various functional relationships will not be known accurately. For our specific application, given the competitive characteristics of the cellular services industry, the sensitivity tests reported here give some confidence that the baseline runs are a useful approximation of reality and the numbers they provide can be used for integrating intangible benefits into the assessment process for this particular project.

Conclusion

In today's cost conscious environment, businesses are justifying their IT projects just like any other investment. The problem is that many of the benefits of such IT projects are so-called intangible benefits, which have stubbornly resisted quantification. They have no material form, but represent value. In this paper, we have suggested a way to put a number on these benefits by using the system dynamics methodology. It rests on the notion of induced observability, which holds that since they represent value, intangible benefits must lead to observable outcomes that are deemed desirable. The SD methodology is used to represent this causal chain in a computational form, and this model can then be used to arrive at a quantitative estimate of the benefit. Intangibles, such as customer goodwill and satisfaction, have value only to the extent that they result in observable outcomes. So we try to model the causal linkage between the two and measure what is observed, as evidence of the benefit. This kind of indirect measurement of a phenomenon of interest is not uncommon, even in the physical sciences. For example, astronomers hold that the universe is expanding. It is not possible to measure this speed of expansion directly. However, just as the whistle of a train sounds lower in pitch when it is moving away from the observer—the well-known Doppler effect—light emitted by stars in an expanding universe will be lowered in frequency when they reach the earth. This so-called red shift can be measured, and from it one can indirectly estimate the speed of expansion based on a model of the Doppler effect (NCSA 1995).

That said, the SD approach to quantifying intangible benefits must be used with appropriate care. The causal relationships that are identified when linking the benefit to its observable outcomes must be defensible on the basis of some evidence, whether theoretical or empirical. Moreover, the functional forms should capture known patterns of the causal effect. Sometimes it is not possible to establish such a causal chain, in which case quantification of the intangible benefit will remain elusive. Sensitivity analysis needs to be performed in order to form an idea of the margin of error in the quantitative estimates generated by such models. In short, generating the SD model for quantification is a non-trivial activity, and there will be imprecision in the numbers that are generated. However, the payoff lies in doing better than simply providing narratives to go along with claimed intangible benefits. Narratives are usually not well received by finance departments which allocate monies based on hard numbers. An approach such as the one presented here is a step toward obtaining credible numbers to support IT project proposals.

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