Working Paper Proceedings

Engineering Project Organization Conference
Devil's Thumb Ranch, Colorado
July 29-31, 2014

Using Tradespaces to Allocate Contractual Risk in Flexible Design Concepts

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Proceedings Editors
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USING TRADESPACES TO ALLOCATE CONTRACTUAL RISK IN FLEXIBLE DESIGN CONCEPTS

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ABSTRACT

Conceptual design in public-private partnership infrastructure projects involves decision-making under risk and uncertainty under the frame of a contract. Both the principal (public sector) and the agent (private firm) must understand how risks affect project value and make decisions about how best to allocate them. The principal and the agent are separated by organizational and institutional boundaries, creating information asymmetry and encouraging adversarial behavior. This work contends that a collaborative boundary-spanning design approach in the project front end will help decision-makers better understand project risks and enhance project value. A tradespace model that represents risk-value relationships can enable decision-makers to span the boundary and collaboratively trade risk in the conceptual design phase. The study first develops a tradespace model for a large desalination plant that relates technical design variable and contractual formulations to project risk and economic performance outcomes Results from the model demonstrate how the principal and agent can trade risk to obtain value. The model is then fitted with an interface for tradespace exploration and used in a design experiment. A repeated measures experimental design with order balancing and time adjustment will be used to test a number of hypotheses about relationships between independent and collaborative design, information asymmetry, and the use of modularity as a mechanism to allocate risk. Experimental data collection includes pre- and post-surveys, concept design and performance data from the model, and protocol data of the design process. Pilot users are currently testing the interface-enabled tradespace model for use in the design experiment.

KEYWORDS: risk, boundary objects, collaborative design, desalination, flexibility

INTRODUCTION

Engineering planning and design for capital investments like infrastructure projects presents a decision-making dilemma. On the one hand, decision-makers tend to be risk-averse in the form of *loss aversion*, where "losses loom larger than gains," making them overly cautious while making risky decisions (Kahneman & Knetsch, 1991). Planners and designers may place a very high premium on preserving the reliability status quo, for example by attempting to meet service requirements at all times and under all conditions. In other words, they subjectively penalize themselves heavily for losses in the form of unmet service, and implicitly encourage overdesign and overbuilding. On the other hand, decision-makers also tend to be unduly optimistic about the outcomes of their decisions when they do in fact engage in new projects. The *optimism bias* reflects typical cognitive heuristics, which may interact with organizational or institutional incentives (Flyvbjerg, 2009). The very caution that leads decision-makers to pursue new projects results in them taking higher levels of risk by optimistically undertaking new risky projects. Loss aversion and optimism bias can interact to result in outcomes such as underutilized

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The author acknowledges funding support from the KACST-MIT Center for Complex Engineering Systems

assets that are in place for unlikely scenarios of very high demand, or prematurely investing in rapidly evolving technologies that are very expensive today, but hold the promise of cost-effectiveness in the future. This dilemma creates the backdrop for a line of inquiry with respect to how engineering planners make decisions in the context of risk in infrastructure projects.

Risk can often be an afterthought in the conceptual system design process (Van Bossuyt, Tumer, & Wall, 2013). Designers often make implicit assumptions about the riskiness of design concepts. In complex systems such as large infrastructure projects, the prevalence and impact of risks is well understood (R. Miller & Lessard, 2001), but recent work suggests that decision-makers struggle to engage the concepts of risk in a way that enhances project value (Ansar, Flyvbjerg, Budzier, & Lunn, 2014). While management may think of risk at the firm level, they rarely evaluate risk at the project level (Graham & Harvey, 2001). Van Bossuyt et al (2013) find that elevating risk to the status of an explicit system design variable in the conceptual design phase helps designers to trade risk against value in their designs. In a multi-stakeholder situation where more than one decision-maker influences the design of the complex system, cooperative information exchange between decision-makers can improve design outcomes when compared to adversarial exchange (Ciucci, Honda, & Yang, 2012). However, decision-makers' risk aversion and organizational boundaries may limit the effectiveness of cooperative information exchange in the conceptual design phase of infrastructure projects.

This work addresses how decision-makers can effectively span boundaries to trade risk during the conceptual design phase in infrastructure projects. Risk is traded and eventually allocated through contracts, in a principal-agent setting. Designers in firms participating in public-private partnership arrangements often encounter such situations in which they are responsible for proposing good technical design concepts, yet they may not be aware or able to contemplate the effects of economic risks on the overall value of the project. Using a large desalination project as the case context for a design task, the study investigates how engineering designers with limited training in economics and finance conceptualize designs when presented with alternative contractual forms for the project concession.

Flexibility in design is one mechanism by which decision-makers can accommodate and shape the risk-value profile by embedding real options in projects (de Neufville & Scholtes, 2011). This work also investigates whether and how engineering designers operationalize flexibility in technical design (real options) by first embedding a capacity expansion option and then by exercising those options in the operational life of the project (Garvin & Ford, 2012), under alternative contractual forms such as fixed price contracts, minimum revenue guarantees, and revenue collars (Shan, Garvin, & Kumar, 2010). The research therefore not only links concession design with technical design, which are mostly treated independently in the literature, but also unpacks how engineering designers perceive this linkage.

The research employs a design experiment (Cardin et al., 2013; Kovacic & Sreckovic, 2013) featuring engineering students as individual experimental subjects who use an architectural *tradespace exploration* or screening model (Ross, McManus, Rhodes, & Hastings, 2010) for evaluating desalination plant designs, under three different contractual arrangements with control and treatment conditions. The Monte Carlo Simulation-based model employs a graphical user interface and simplifies the cognitively burdensome task of exploring a complex multi-dimensional tradespace – a design space with some performance tradeoffs among design concepts measured along different dimensions – with risk factors (Van Bossuyt et al., 2013). The model is an interdisciplinary boundary object, since it transforms engineering designers' technical design choices into economic performance outcomes with real-time feedback on design

choices. Participants are drawn from a pool of advanced degree systems engineering students with work experience and courses in systems design to mitigate concerns of differences between expert and novice designers (Cagan et al., 2013).

The next section of this paper covers relevant threads in the literature and sets up the main line of investigation. The section on methodology then presents the project case context and analytical underpinnings of the tradespace model, followed by an overview of the experimental design. Some preliminary analytical results are discussed, and the status of the investigation is summarized.

LITERATURE

The dilemma of decision-making under risk presented here is not limited to engineering approaches, but it may take a specific form in engineering design. Many authors have long argued that delusions of success and illusions of control are prevalent (Donaldson & Lorsch, 1983; Lovallo & Kahneman, 2003; March & Shapira, 1987) because managers and executives don't think of risky decisions as gambles. They view risk as a challenge to be overcome and believe they have some agency and a degree of control within projects to obtain favorable outcomes. In a similar way, engineers may look for ways to exercise control by making design decisions and shape the risk-outcome space in project's favor. In doing so however, they may make poor judgments because of their human *cognitive bounds*: bounded rationality, bounded awareness, or bounded self interest (Bazerman & Moore, 2013); interacting with their deeply ingrained *occupational culture*: design experience, problem solving approach, reductionist thinking and heuristics such as safety margins (Godfrey & Parker, 2010; Kahneman, Lovallo, & Sibony, 2011); *organizational frames*: specific planning approaches or pressure to succeed within an organization (Eckert & Clarkson, 2010; Fellows & Liu, 2013; Leonardi, 2011); and *social or institutionalized processes*: incentives to meet normative performance standards for safety or reliability outcomes that shape decision-making .

Cognitive perspectives on decision-making under uncertainty in project investments suggest that decision-makers exhibit systematic biases (Ansar et al., 2014) and they are often prone to excessive optimism. The decision scientist Kahneman and his colleagues suggest that optimism and the "planning fallacy" (Kahneman & Lovallo, 1993; Kahneman et al., 2011) are a consequence of taking the *inside view* on project decisions, by focusing exclusively on the project at hand and extrapolating current trends. In other words, decision-makers tend to ignore the historical experience of similar projects or to think about them statistically; doing so would be to take the *outside view*. These authors suggest that "reference class forecasting", i.e. using a large sample of projects as a reference for benchmarking, can provide the missing outside view.

The occupational culture in engineering planning and design often revolves around designing to pre-specified requirements. This approach to design can be a limitation in the context of risk, since project needs and concepts are often co-evolving in the front-end phase. Locking in specifications or requirements can therefore lead to technology obsolescence and underutilized assets. The literature on real options suggests that decision-makers can defer certain types of decisions, and remain flexible along certain design dimensions by embedding real options in projects. However, many authors have observed that there are significant barriers to adopting a real options approach since designing with risk in mind is often not an explicit objective (Cardin et al., 2013; Garvin & Ford, 2012; K. D. Miller & Shapira, 2004). Engineering design training and perspectives may reinforce this occupational culture.

Organizational forms (Gann & Salter, 2000) and institutional requirements (Gómez-Ibáñez, 2003) create boundaries between the users of an infrastructure project on the one hand and its designers, builders and operators on the other (Bechky, 2003; Fong & Kwok, 2009; Leonardi, 2011). Since these boundaries separate information, disciplines, roles and responsibilities, decision-makers may lack a shared point of reference in the decision-making process. A boundary object is thus any artifact that enables decision-makers to reach common understanding about an issue, since it provides a common frame of reference and a specific vocabulary for information exchange (Iorio & Taylor, 2014). In the infrastructure space, boundary objects take the form of bid documents, design drawings, 3D models, and can assist decision-makers negotiate contracts (Koskinen & Mäkinen, 2009). To do so, decision-makers implicitly or explicitly focus on identifying and allocating risks.

Institutional norms for transparency and efficiency in project procurement often set up principal-agent contexts. In the ideal, incentive contracts govern behavior in principal-agent settings. In infrastructure projects, the principal is often a public sector agency whereas the agent is a project firm (or consortium of firms coordinating actions). The interest of the principal is to obtain its project efficiently (by maximizing value or minimizing costs) while the agent wants to maximize its profits (Puddicombe, 2009). "Arms length" transactions in the form of the contract are the norm to support competitiveness and market behavior (Koskinen & Mäkinen, 2009), and there are clear boundaries between principals and agents and institutional restrictions on how they may share information. Although there is extensive work on the design of contractual incentives to elicit optimal behavior from agents in infrastructure projects (Hampson, Parsons, & Blitzer, 1991; Shan et al., 2010), decision-makers may struggle with how to identify, perceive and manage risks in infrastructure projects (Marle & Vidal, 2011; Maytorena, Winch, Freeman, & Kiely, 2007; Thomas, Kalidindi, & Ananthanarayanan, 2003). This may often lead to myopic decisions. Nonetheless, principals and agents are still left with the task of understanding and allocating risk in the early design phase of projects, and they may need to collaborate closely and share information across boundaries in a way that helps them achieve common understanding.

This study proposes the use of a tradespace model as a boundary object. A tradespace model is a high level (low fidelity) model that relates the attributes of conceptual designs to their expected performance outcomes along multiple dimensions (Van Bossuyt et al., 2013). Designers look for high performing designs, defined using one or more performance or value metrics, by trading attributes in the design concept. For example, a car designer may reduce a car's power and weight to increase its mileage to enhance the design concept's performance along the efficiency dimension. Tradespaces can thus effectively screen out low performing design concepts, retain high performers, and help decision-makers understand trade-offs among high performing designs using representations like a *pareto front* (Ciucci et al., 2012).

To summarize, conceptual design in infrastructure projects requires decision-making under risk. Cognitive effects and occupational culture may influence these decisions. In a principal-agent setting, a contractual frame creates the structure for decision-making. Principals and agents must span organizational boundaries under a contractual frame to shape the risk-value relationship in projects, through mechanisms such as flexibility in design (real options). This investigation posits that decision-makers in this setting can mitigate cognitive limits and span boundaries by collaborating through the use of a tradespace model. They can better allocate risk in project concepts by developing a shared understanding of how project designs affect value.

METHODOLOGY

This section develops the main and supporting hypotheses for the work. It also discusses the case context for the design task and development of the tradespace model, as well as the experimental design setting.

Hypothesis development

Consider a simple example that illustrates the value of linking design concepts to their risk profiles and expected performance outcomes using a tradespace model. Figure 1 shows representations (cumulative probability or target curves) of performance and risk for two different design concepts for a large infrastructure project, a desalination plant, under an identical fixed-price concession contract. The first design is a large monolithic plant (1 unit; 50,000 cu.m./day) and the second design is an even larger but modular design (10 units; 180,000 cu.m./day). Both plants employ the same reverse osmosis technology and have identical operating characteristics. Project operation is simulated under a risk profile with only one risk factor – water demand uncertainty (2% annual growth, 5% annual volatility) – using a Monte Carlo simulation with 10,000 iterations. Project performance is measured in multi-objective terms: the agent's objective is to maximize net present value of profits, whereas the principal must minimize the expected value of nonserved demand due to water shortages, a proxy for social welfare. From the 'project present value' chart on the left, we observe that these two design concepts have the same expected value performance outcome (Net Present Value ~ $ 90 million) for the agent but very different risk profiles for both the principal and the agent. The 'nonserved demand present value' chart on the right measures the value to the principal, and shows that the modular design has a very short left tail, drastically reducing downside risk to the principal. In fact, the modular design also increases the upside for the agent – there is approximately a 20% probability that the modular design will increase the value of the project to the agent relative to the monolithic design. In short, the modular design is a pareto improvement since it improves outcomes for both the principal and the agent.

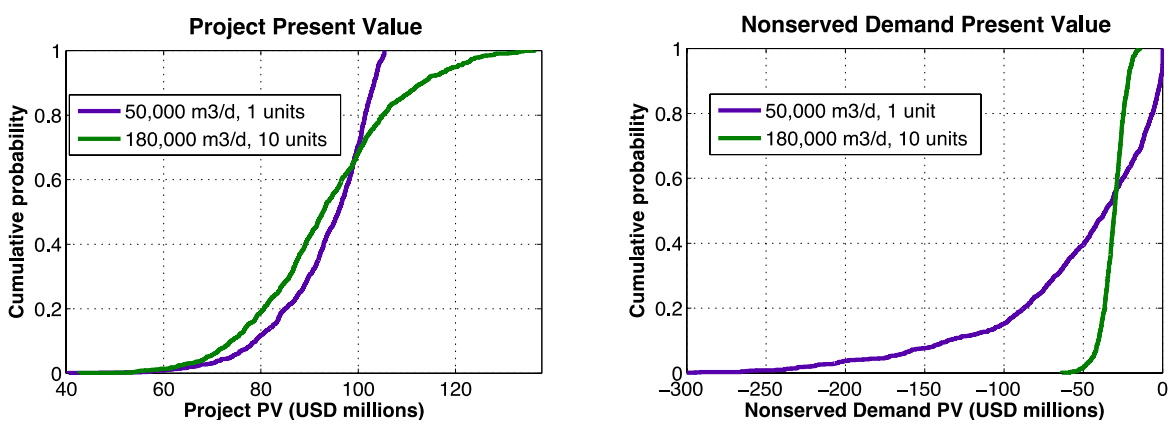


Figure 1. Cumulative distribution functions as representations of risk to the agent (left; NPV as a metric) and the principal (right; nonserved demand as a metric) under an identical fixed price contract for a new desalination project.

This example demonstrates how a tradespace model can relate risk to performance for different conceptual designs in an infrastructure project. If the principal and agent can explore

the design space collaboratively, there may be a higher likelihood of them trading risk in favor of value to obtain pareto outcomes. Thus the main high-level research question of this work is:

How can decision-makers collaboratively use a tradespace model to allocate risk by developing flexible design concepts?

The main hypothesis of this investigation follows:

H*main*: a principal and agent can converge to flexible pareto design outcomes with the use of a tradespace model that gives them a shared understanding of the risk-value relationships in a project.

An appropriate test of this hypothesis must involve a condition where decision-makers are acting independently, i.e. not collaborating, for a true comparison of how they approach the design activity without boundary spanning). While acting in an independent frame, decision-makers may tend to myopically focus on their own objectives and interests. In other words, conceptual designs will optimize single objectives rather than multiple objectives. This is plausible because independent decision-makers may have limited information about how their judgments affect the interests of other parties, since organizational boundaries and institutional rules create information asymmetries. It is also plausible that they would continue to act myopically even if they had more information about the other decision-maker's objectives because there is no process or incentive for trading. Further, since independent design does not create opportunities for iterative or traded designs, decision-makers will tend to quickly identify conceptual designs than if they were to collaboratively assess concepts.

The following framework in Figure 2 captures the concepts that this work intends to study in the context of the research question formulated above. The framework has two independent dimensions: a *design process* dimension with 'independent design' and 'collaborative design' as its two levels, and a *boundary-spanning* dimension with the two levels of 'information asymmetry' and 'common knowledge'. This factorial framework lends itself to an experimental design formulation, discussed later.

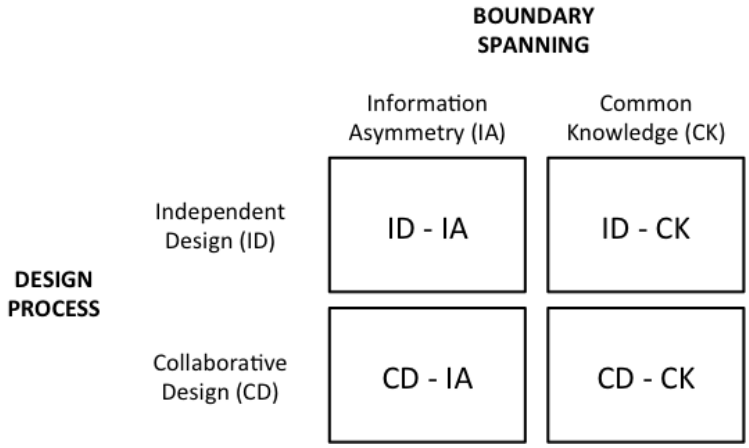


Figure 2. Conceptual framework for testing the role of collaborative design for boundary spanning

The example above also demonstrates the use of modularity as a mechanism for improving project value in the context of risk. Modular designs are capacity expansion options – they add value because decision-makers may defer the decision to install additional output capacity (delaying capital expenses) until and only when high demand scenarios are realized. In other words, this type of flexibility is valuable because decision-makers can closely match output capacity to demand. We therefore also posit hypotheses about the use of modularity (flexibility in design) in allocating risk through conceptual designs.

The particular shape of the risk profile and the overall-risk value relationship also depends on the design of the concession contract. The price terms and duration of the contract, and any incentives for contingent decision-making can affect the availability of output capacity, which in turns influences the extent of non-served demand.

When the project bears the full exposure to risk factors such as water demand risk, firms (agents) may select design concepts that myopically reduce their risk exposure (variance of performance for a design), for example, by selecting small monolithic plants. They may do so irrespective of whether they know the effect on the principal's objective. When they have limited downside exposure through the contract, they may be more likely to reduce exposure by selecting pareto designs through the mechanism of modularity.

We posit the following specific hypotheses about (a) myopia, (b) information asymmetry, (c) duration, and (d) modularity during independent and collaborative design.

H1a-d: In independent design, conceptual design outcomes are (a) myopic, (b) irrespective of information asymmetry, marked by (c) shorter durations of tradespace exploration, and (d) predominantly monolithic

H2a-d: In collaborative design, conceptual design outcomes are (a) pareto (b) affected by information asymmetry, marked by (c) longer durations of tradespace exploration and concept convergence, and (d) predominantly modular.

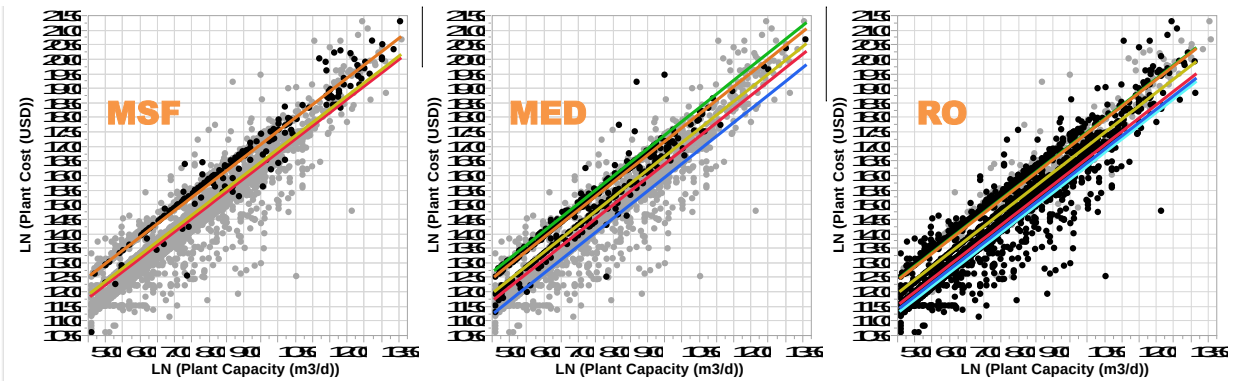
We have used a simple analytical example of relating risk and value in the conceptual design of a desalination project to posit hypotheses about the nature of outcomes, information asymmetry, duration of tradespace exploration and the use of modularity as a mechanism to shape the risk-value relationship.

Design case context: desalination

The design task is to conceptualize designs for a water desalination plant. The available choices for the design are three technologies (reverse osmosis - RO, multi-stage flash - MSF, and multi-effect distillation - MED). The technologies have different capital and operating costs. Reverse osmosis is an electromechanical technology, using electricity to drive water under high pressure through a membrane. The latter two are thermal distillation technologies. They use heat from the combustion of fossil fuels like heavy fuel oil to evaporate water. Another important design choice is the level of water production capacity of the plant, where *plant capacity = unit capacity x number of units*. The plant capacity can therefore be scaled by increasing unit capacity to some extent, and then by the number of units. Plants are thus flexible in terms of their capacity, because they can increase or decrease in unit size, and then can be modular in terms of

the number of units. This flexibility can contribute to the value of the project when the demand for water is uncertain.

To avoid concerns of optimism bias and bidding strategies around cost parameters in the experimental part of the work, we first developed a "reference class" of desalination projects to assess capital costs and other structural attributes of desalination projects. Figure 3 shows regression results for capital cost relationships in a dataset of almost 7,000 desalination projects executed globally in the period 1980 – 2013. While the data covers all three technologies mentioned above (N_{MSF} = 195; N_{MED} = 655; N_{RO} = 6,102), about 85% of the projects employ RO.



	Multi-Stage Flash (MSF)	Multi-Effect Distillation (MED)	Reverse Osmosis (RO)
Sample Size (N)	195	655	6,102
adj R^2	0.95 ***	0.96 ***	0.94 ***
Intercept = LN (A)	7.87 ***	7.76 ***	7.67 ***
Unit Size (Alpha)	0.92 ***	0.94 ***	0.92 ***
Units (Beta)	0.89 ***	0.98 ***	0.94 ***
Tap (< 500 ppm)	-	-	-0.56 ***
River (500 ppm - < 3,000 ppm)	-	-0.78 **	-0.45 ***
Brackish (3,000 - < 20,000 ppm)	-0.29	-0.31 ***	-0.30 ***
Seawater (20,000 - 50,000 ppm)	0.45 **	0.46 ***	0.58 ***
Brine (> 50,000 ppm)	-	0.67 ***	0.60 ***

***:#p<0.0001
#*##p<0.001
##:##p<0.01

Figure 3. Capital cost regressions for the main desalination technologies using a Cobb-Douglas production function relationship (trends are linear because of log-log scale)

The data includes values for total plant output capacity (cubic meters / day) and the number of modules at each plant site, so that output capacity of each modular unit can be calculated. After testing a number of relationships, the following Cobb-Douglas formulation was found to provide the best fit using a log-log linearized transformation while controlling for input feedwater quality (Total Dissolved Solids – TDS).

$$Capital\ Cost = A * (module\ capacity)^{\alpha} * (number\ of\ modules)^{\beta} \qquad (1)$$

where A is the intercept to capture the aggregate effect of various structural and locational attributes, is the power relationship for the effect of module capacity on overall capital cost for a technology, and is the power relationship for number of modules on capital cost. As Figure 2 shows, these relationships are statistically significant (at the $p < 0.0001$) level with about 95% of the variations in cost explained (adj. R^2 ~ 0.95) across different feeedwater qualities. These capital cost relationships, and technical efficiency factors and operating cost data (with energy price uncertainty) obtained from literature are used to parameterize the tradespace model discussed below.

In addition to the technical design dimensions, a contractual layer represents the project organization and relates cash flows to risk and overall economic performance. Three contract forms are available as a contractual design dimension – a fixed-price contract, a minimum revenue guarantee contract, and a revenue collar contract. In the fixed-price contract, the project receives a fixed $/cu.m. of water delivered, which depends on the realized demand for water. The project bears the full extent of the demand risk.

Under a minimum revenue guarantee, the project receives a lump-sum payment irrespective of the demand for water upto a certain capacity threshold. Above the threshold, the payments revert to a fixed $/cu.m. structure. The project sees less downside risk than in the case of the fixed-price contract because the lump-sum payments cover a fraction of its costs. It also still sees all the upside in the event of high demand scenarios.

The revenue collar contract augments the minimum revenue guarantee with a revenue ceiling. It continues to reduce some of the downside of low water demand, but also caps the upside. Between the ceiling and the floor, the project receives a fixed $/cu.m. payment.

These contractual formulations are included as a contracts design lever in the tradespace model, discussed below.

Tradespace model development

The tradespace model is a multi-objective screening model that reduces a very large design space – a set of many feasible possible plant designs – to a much smaller set of "attractive" designs that meet the key objectives or design criteria. The model takes as inputs locational water quality attributes, and information on water demand and energy price uncertainty, and investigates how these economic factors and contract structures interact with technical design features under uncertainty. The screening model attempts to simultaneously relate the economic asset value (for the agent), to the social loss (value to principal) due to water shortages.

The formulation of the tradespace model must consider some important contextual issues such as the difficulty in assessing the economic value of water, uncertainty in water demand and energy prices, the relationship between these factors, and the types of design decisions that the principal and agent may want to make in terms of plant technology, plant capacity, contract duration, etc.

Since there is no market-based economy-wide water price, decision-makers cannot directly observe the marginal value of supplying an additional cubic meter of water. The opportunity cost of water from alternative uses can be used as a proxy as could the residual value of water as an input, but calculating marginal value sector by sector, or by application is problematic. Another option is to simulate a "market-like" setting for the water produced by a desalination facility; the tradespace model currently uses this approach to simulate a water price.

Aggregate demand for water fluctuates from year to year but grows at some expected rate in the long run. Most planning forecasts for water needs do not introduce uncertainty or volatility in projections. If the value of water is related to uncertain demand in someway, then water price should also be volatile over time because of demand variations. When the users of water can observe the (market) value of water, they can decide whether to use water based on its cost to them relative to its value. Since water is essential in many ways (high value of using it) and since users cannot observe its price/cost, demand is relatively inelastic. The price of water then also depends on the capacity available to meet demand.

The mathematical formulation for the "market-like" setting for the water produced by a proposed desalination facility accounts for these issues, and is written as an inverse demand function model of the form (Grenadier, 2000):

$$P(q(t), X(t)) = X(t)Q(t)^{(-1/g)} \tag{2}$$

where P(t) is the instantaneous price, X(t) is the instantaneous demand, and Q(t) is the available production capacity in that instant. The quantity γ is the constant elasticity factor. The tradespace model first uses this "spot price" to inform investment decisions and then later enables contract structures to determine the revenues and cash flows.

For the fraction of demand in the economy that is to be supplied by desalination, the value of meeting demand is thus related to the available desalination capacity. If demand levels are below installed capacity, then all the demand can be met and the capacity constraint is non-binding. While water price may fluctuate, it will remain relatively low because there is available/excess capacity, and the cost of producing desalinated water may also exceed the price. When demand approaches the capacity constraint or exceeds it, the system experiences shortages. In such situations, the price of water should rise to reflect the shortage (scarcity value). High water prices in the event of a binding capacity constraint are a signal to invest in additional desalination capacity.

In theory, the principal can select all investments and their timing. Centrally planned infrastructure investment problems are typically formulated using cost-minimization as the objective. This is one way to proceed. Since the principal is aware of all the investment possibilities, it can choose that portfolio of projects that minimizes the costs for the system. However, as we have discussed above, the cost of delivering water is different from its price, which depends on demand in relation to available capacity. So a minimum cost investment may not be the same as a value maximizing investment. Another way to proceed is to examine and relax the reliability assumption (loss aversion) in which the principal selects the level of investment that meets demand completely (100%, all the time) and then configures the discrete assets in the portfolio to meet the chosen investment level in a least cost way. Under this assumption, the system often has excess underutilized capacity. Instead of ensuring that all demand is met (which is very difficult under demand uncertainty), the principal could instead focus on the outcome of underinvesting in capacity, i.e. reducing shortages, which create a social loss for the system. Figure 4 shows a schematic of the tradeoff of excess capacity (overinvestment) and shortages (underinvestment) for a demand trend that grows over time.

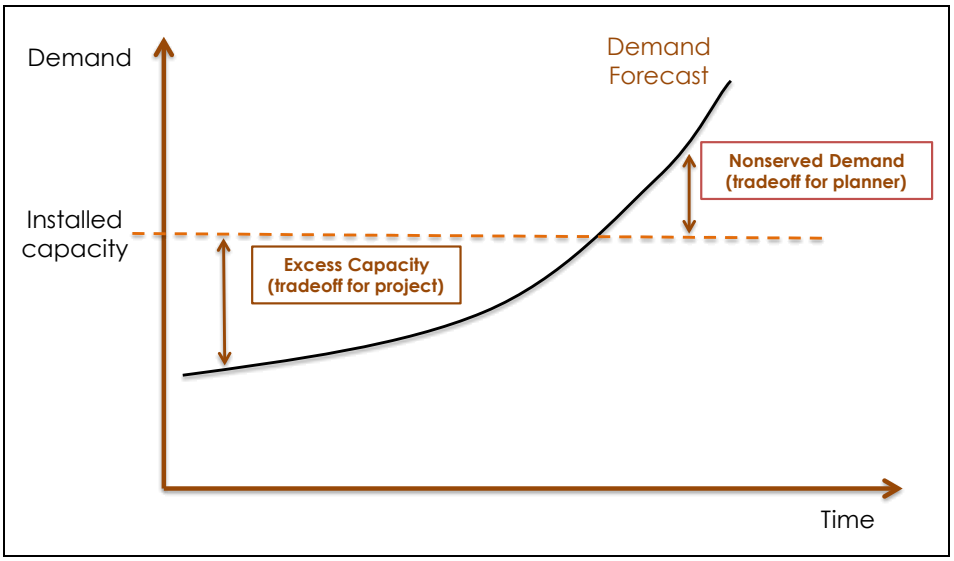


Figure 4. The level of installed capacity determines whether there is a capacity shortage (nonserved demand for the principal) or there is excess underutilized capacity (a sunk investment cost for the agent)

In this formulation, the principal's problem is to maximize the system value function, given by:

$$J(W_0) = \max_{Q} \quad E\left[\int_0^T e^{-rt} S(t) - \sum_i K(DQ_t) e^{-rt} \,\middle|\, W(0) = W_0 \right] \tag{3}$$

where S(t) represents the "social surplus" - the value to society of meeting demand at a certain price, with the available installed capacity Q(t). Equation 3 and Figure 5 below show how the surplus is calculated in relation to these variables.

$$S(t) = \int_0^{Q(t)} P(q)\,dq - \int_0^{Q(t)} O(q)\,dq = \int_0^{Q(t)} X(t) Q(t)^{(-1/g)}\,dq - \int_0^{Q(t)} k(t)\,dq$$

$$S(t) = \frac{g}{g-1} X(t) Q(t)^{g-1/g} - k(t) Q(t) \tag{4}$$

The last summation term in Equation 3 denotes the investment program, i.e. the schedule of investments and costs incurred for all the instances when the principal adds capacity. The economic flows in this problem are discounted at a rate r. Since the principal is maximizing the expected value, this formulation probabilistically considers the effect of uncertainty in the simulation.

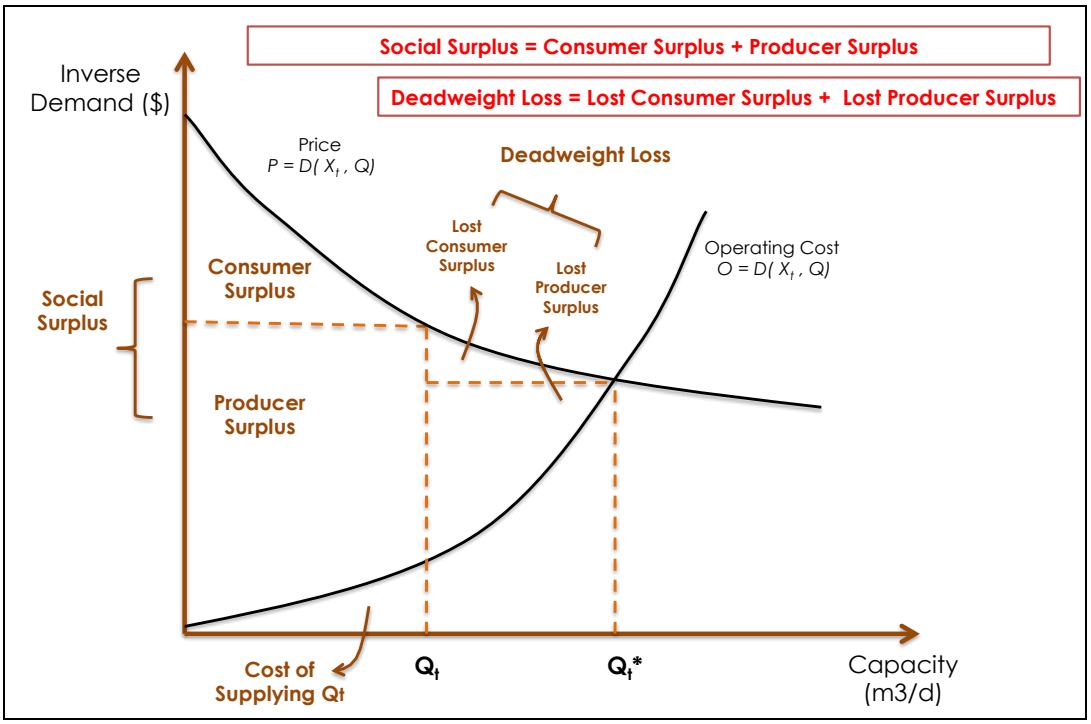


Figure 5. The principal's objective is to maximize social surplus, or minimize the deadweight loss of shortages at every instant in time. The weighted summation of outcomes over the life-cycle of the design for every scenario tested given the value accruing to the principal and the agent.

In this problem, the planner may be averse to the risk of supply shortages for political and social reasons. One limiting case is zero shortages (very expensive due to excess capacity) and the other type of extreme is very high shortages (high social losses). However, this calculation is non-linear and a characteristic of the risk-aversion. Very small frequent supply shortages at relatively low prices (and excess underutilized capacity) are more acceptable than drastic large shortages at high prices (with underinvestment). By using the market formulation above, the tradespace model can identify conceptual designs (investments) that minimize the cumulative present value of instantaneous shortages adjusted for time and risk by discounting.

In some cases, the principal may not make all the investments, and to preserve an arm's length relationship for regulatory and structural reasons, there may be a private firm that must select the level and type of investments under a contract. The principal would nonetheless like these agent firms to make investments in design concepts in line with the objective of minimizing the lost value due to shortages. The same investment problem can then be described in a principal-agent formulation where the planner still wants to minimize nonserved demand (Equation 5), whereas the firm wants to maximize its economic profit in terms of the net present value (NPV) of the investment (Equation 6).

$$Nonserved = \min_{Q} \; E\left[\int_0^T e^{-rt} DWL(t)\right] = E\left[\int_0^T e^{-rt}\left(\int_{Q(t)}^{X(t)} P(q)\,dq - \int_{Q(t)}^{X(t)} k(t)\,dq\right)\right] \tag{5}$$

$$NPV = \max_{Q} \quad E\left[\int_0^T e^{-rt} p(t)\right] = E\left[\int_0^T e^{-rt}\{P(Q(t),X(t))*X(t) - k(t)*X(t) - K(\Delta Q(t)\}\right] \tag{6}$$

The multi-objective nature of this problem suggests that there should be trade-offs between the principal's and the agent's preferred designs. In other words, some designs will easily help the principal minimize shortages, whereas others may help the agent firm maximize NPV. The tradespace model can be executed in optimization mode to quantify this trade-off.

Tradespace exploration interface

In addition to the automated analytical mode, the tradespace model also has a Graphical User Interface (GUI) for user interaction, shown in Figure 6 below. This allows a user to select values for design variables and immediately observe a design concept's expected performance and risk representations.

The user interface presents the user with all the relevant information on a single screen The interface has a panel for technical design variables as well as contractual formulations. Performance outcomes for point designs are visualized using probability distributions (PDFs) for net present value, cumulative distributions or target curves, which update with every new concept tested. One set of graphs retains expected performance outcomes for every design tested to allow designers to remember and compare design concepts previously evaluated.

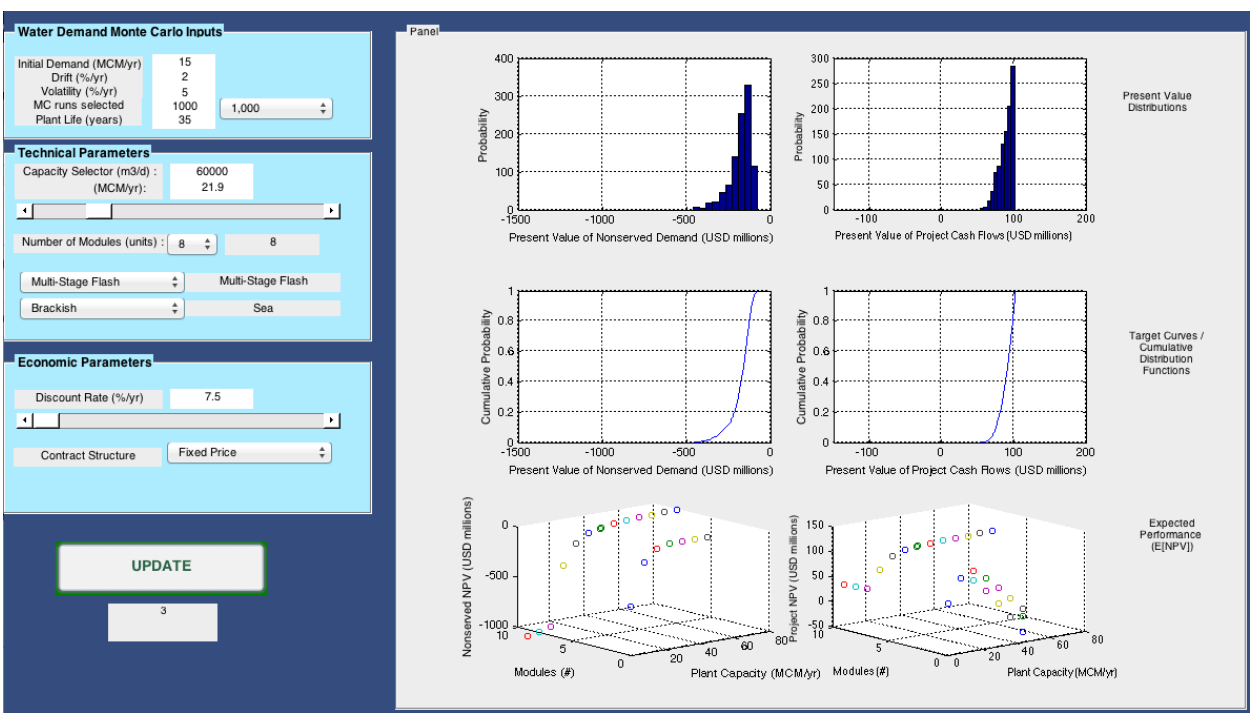


Figure 6. The collaborative design variant of the tradespace GUI showing technical and contractual design variables, as well as risk and expected performance outputs for design concepts

Since the model employs Monte Carlo simulations with 10,000 iterations for water demand uncertainty and energy price uncertainty, computational effort was initially a concern.

However, the model can update results for a new design concept in less than 1 second on an ordinary laptop.

In order to test the effect of collaborative design, a number of variants of the GUI are used so that information asymmetry can be introduced or mitigated for independent design, and with the collaborative version being identical for collaborative designers. The design experiment for testing the role of collaborative design employs this GUI-enabled tradespace model, as introduced in the next section.

Experimental design

The experimental design for testing the role of collaborative design in risk allocation and boundary spanning is a *repeated measures* experiment with *order balancing* and *time adjustment* (Chow, 2010). Figure 7 shows a schematic of the experimental design. Measures are repeated because all subjects are exposed to all experimental treatments. Since there is a threat that the order of administering the treatments may confound results, the order of treatments is switched to assess the effect of order for a fraction of the subjects (50% by random assignment). In such experiments, it is also plausible that the time allotted for completing the design task may affect the outcomes because of an experimental learning effect. By allowing a fraction of subjects (say 50% by random assignment) to spend more time on the design tasks, the experiment can account for the effect of time.

The experiment employs a convenience, but purposive sample of graduate students from advanced engineering design courses who are familiar with common issues in systems design. A Bachelor's degree in science or engineering is a minimum requirement, with no specification on the graduate major, age, gender, or prior work experience. The experiment should capture at least 40 observations for statistical significance of results. The repeated measures design with order balancing and time adjustment therefore requires that 20 observations come from the order switched sub-sample, and 50% of those samples, i.e. 10 observations to have a longer time allotment. Collaborative design requires at least two participants per observation, one to play the principal's role, and one to play the agent's role, calling for a total of 80 experimental subjects.

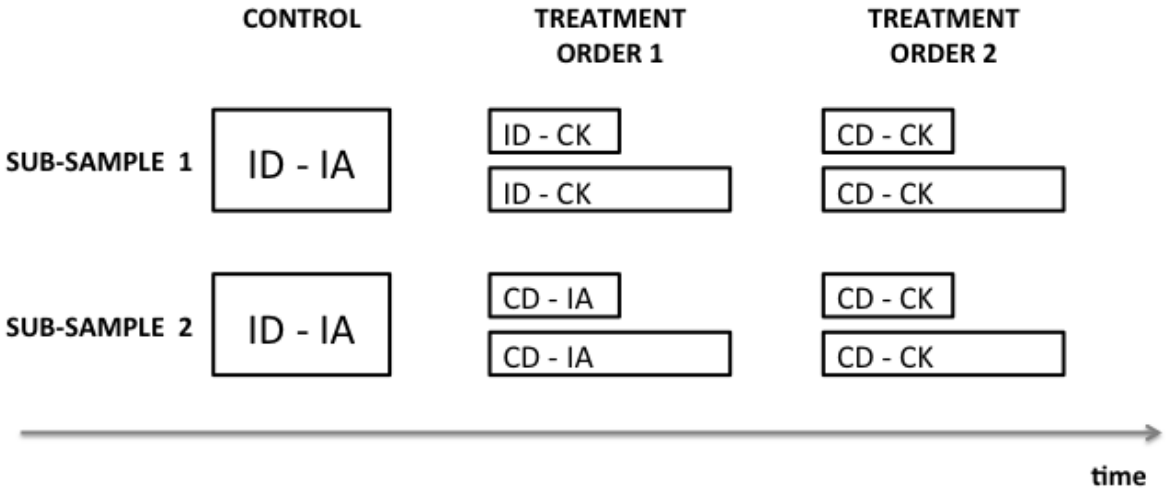


Figure 7. Repeated measures experimental design with order balancing for treatments and time adjustment for learning effects

The experiment collects three types of data: pre- and post-*survey* data, design task *performance* data on design attributes and their translated outcomes in the tradespace model, and *protocol* data on the design process itself. The pre-test survey collects de-identified demographic and profile information (age, background, work experience, etc) as well as Likert-scale questions on subjects' experience with design, *ex ante* beliefs about risk, and expectations for the design task. Before the experiment begins, the facilitator obtains consent and gives each pair of subjects separate task sheets (one each for principal's and agent's roles) that explain the objectives of the design task, the role of the subject, and the types of data and mechanisms for data collection. The facilitator then introduces subjects to the DesalDesign tradespace model tool and allows them to become familiar with its interface and functionality. No performance or process data is collected during this time. After the facilitator has answered any questions, the experimental rounds begin.

Performance data includes attributes of designs evaluated (considered but then rejected) as well as the concept finally chosen. This data is automatically recorded by a video capture of participants' screens as they explore the tradespace through the DesalDesign tool. Participants are asked to submit their final design concepts to the facilitator at the end of each round. Statistical analysis of the performance data is used to evaluate the experimental hypotheses discussed earlier using differences in means and main and simple effects analysis.

Protocol data (Cagan et al., 2013) about the design process becomes important in the rounds that involve collaborative design. Communication between the principal and the agent is captured in the ThinkTank software that stores communication transcripts of all messages exchanged between participants. This avoids the burden of accurately capturing audio (identification risk) and then transcribing verbal data, and mitigates concerns of how subject personalities may influence the design process. A tradeoff is that participants may have to communicate clearly and effectively through their message windows. Content analysis of protocol data is used to descriptively understand the quality and nature of communication in the collaborative design process.

At the end of the experiment, subjects complete the post-survey that addresses their ex post beliefs about risk, the efficacy of the tradespace model for evaluating and selecting design concepts, the communications process between principal and agent, and their overall response to the design experiment.

PRELIMINARY RESULTS

The work described here has progressed to a stage where the tradespace model can be used independently in analysis (separate from the design experiment) to generate some insights about the design problem.

The tradespace analysis provides some intuition regarding risk and performance. Regression analyses of the "reference class" dataset suggest that economies of scale exist for very small plant capacities (up to 10,000 cubic meters/day of potable water) but are exhausted for mid-scale plants (20,000 – 30,000 cubic meters/day). Modular plants with mid-size units can therefore be most profitable since there are no returns to scale from increasing size upfront, when faced with uncertain water demand, while allowing for capacity expansions. This insight is consistent with other empirical observations in the literature, and gives rise to an experimental hypothesis that after observing the NPV performance in the training round, 'the agent will initially propose mid-size plants under water demand uncertainty and fixed price concessions'. The tradespace model also shows that for mid-size plants a fixed-price concession allocates the water demand risk to the agent. It will therefore 'under-invest initially and then exercise capacity

addition options in a way that lags demand'. The minimum revenue guarantee allocates some of this demand risk to the principal, so the agent should 'initially over-invest, but also enable and exercise capacity options to take advantage of the upside' when water demand is high. Under a revenue collar, the upside for the agent is truncated by the ceiling of the collar, hence 'the agent will over-invest initially, but limit capacity expansion options' since their revenue is capped. These dynamics may be observed in the experimental setup described above.

Results from the current version of the tradespace model do in fact reveal design tradeoffs. Figure 8 shows the pareto trade-offs in two different settings. The chart on the left shows a situation where the agent firm is investing in a monolithic ('No Modularity') desalination facility of a chosen technology (Reverse Osmosis) under a fixed price water purchase contract ($/m3 delivered), and the firm can vary the production capacity of the plant as an independent variable. The horizontal axis shows the project's profitability (NPV) for the firm, whereas the vertical axis denotes the social losses (nonserved demand) as a consequence of the selected level of capacity. The chart has three different curves for differing degrees of volatility (0%, 5%, 10%) in the demand for water from that plant. In general, points to the top left of the chart indicate levels of capacity that minimize social losses, and points to the bottom right suggest those that maximize firm NPV. The analysis suggests that as NPV increases, the social losses also increase, because of the trade-off between the two objectives. We observe this result irrespective of the degree of volatility in demand; however, for higher levels of volatility there are many levels of capacity that meet one objective but not the other. Figure 9 represents the designs that generate these pareto fronts in a two dimensional design space where total plant capacity is on the horizontal axis, and the number of modules is on the vertical.

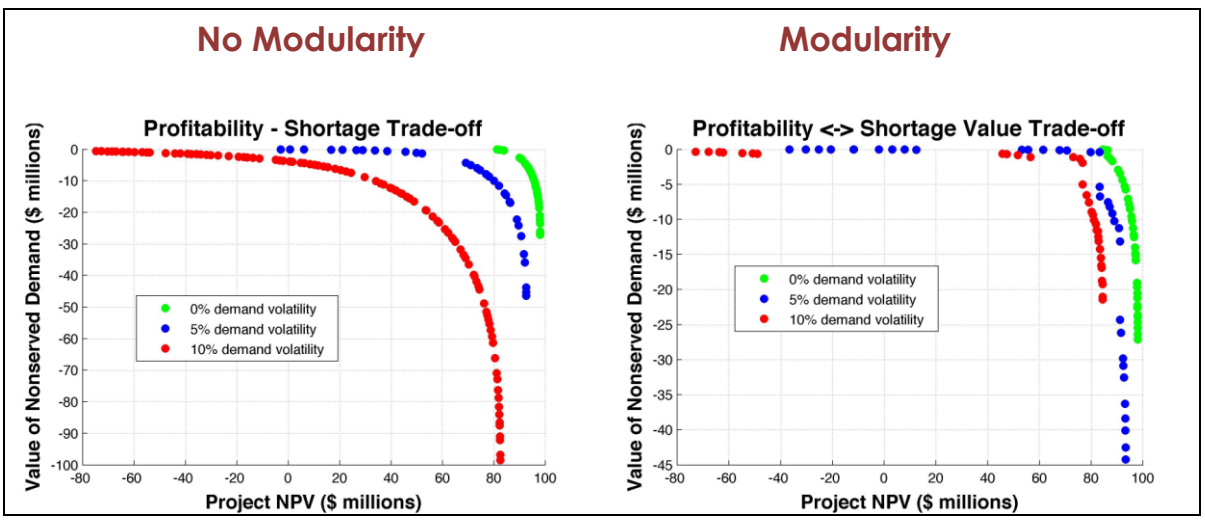


Figure 8. Pareto trade-offs in monolithic/non-modular (left) and modular (right) plant designs, with modularity presenting knee points that simultaneously maximize project NPV and minimize the social losses of nonserved demand

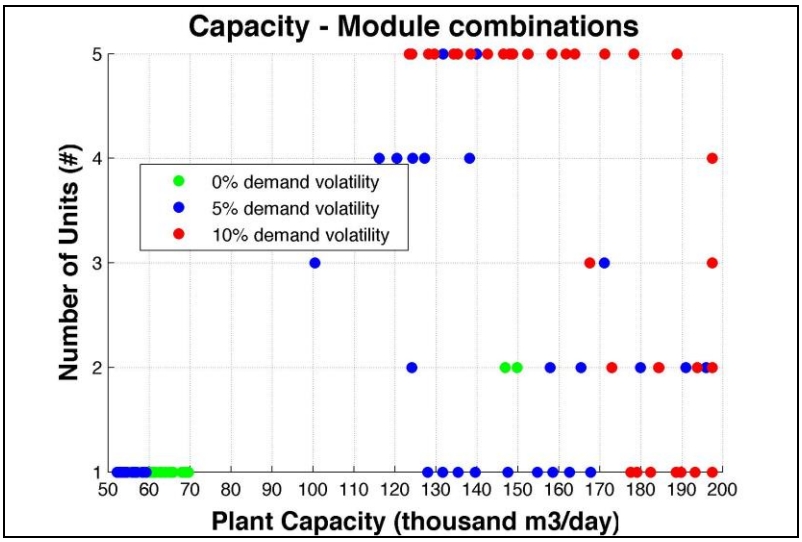


Figure 9 Designs that are pareto optimal in terms of maximizing firm's NPV and minimizing social losses

The GUI-enabled model is currently being used in pilot runs of the experiment to resolve any conceptual and technical issues, and to observe how users interact with the model.

SUMMARY

Conceptual design in infrastructure projects with public-private partnership arrangements requires decision-making under risk. In a principal-agent setting, a contractual frame creates the structure for decision-making. Principals and agents must span organizational boundaries under a contractual frame to shape the risk-value relationship in projects, through mechanisms such as flexibility in design (real options). This investigation posits that decision-makers in this setting can mitigate cognitive limits and span boundaries by collaborating through the use of a tradespace model. They can better allocate risk in project concepts by developing a shared understanding of how project designs affect value. Through a simple conceptual example, the main hypothesis on collaboration is partitioned into specific hypotheses for eventual testing in a design experiment. The analytical background of the tradespace model is covered and its results provide some intuition for how experimental subjects may behave in the design experiment. Experimental subjects can explore the tradespace using an interface, in a repeated measures design that accounts for treatment orders and learning effects. The model is under pilot testing for use in the experiment.

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