INTERNATIONAL DESIGN CONFERENCE - DESIGN 2016
Dubrovnik - Croatia, May 16 - 19, 2016.

USING CONTESTS FOR ENGINEERING SYSTEMS DESIGN: A STUDY OF AUCTIONS AND FIXED-PRIZE TOURNAMENTS

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Keywords: crowdsourcing and funding, game theory, systems engineering (SE)

1. Introduction: contests in engineering systems design

Recently, there has been an increasing interest in using open innovation mechanisms, such as crowdsourcing, within product development processes [Innocentive.com]. Crowdsourcing involves outsourcing of tasks to a large network of unaffiliated individuals outside the traditional organizational boundaries [Howe 2008]. Employing online communities through the Internet has made it possible to bring in intellectual capital from outside as needed [Chesbrough et al. 2006]. Crowdsourcing is typically carried out in the form of contests where a problem is announced, along with a prize amount for the best solution.

The use of crowds for innovative design and problem solving is not new. For example, tournaments have been carried out since 1700's. The British government, in 1714, offered a monetary prize to come up with a way to measure a ship's longitude. Sub-contracting by large organizations such as GE [2009] and NASA [2001] is carried out using this approach. It is well known that the solution quality is dependent on the incentives, and the structure of the contest [Terwiesch and Xu 2008]. For example, individuals may not participate if the prize is low, or they may invest less effort if large numbers of other participants are participating, because of the reduced winning probability. Designing good crowdsourcing contests necessitates understanding how incentives affect solution quality, how individuals decide whether or not to participate in the contest, how much effort to invest, etc. There is currently a lack of understanding on how to organize such crowdsourcing and open innovation activities for engineering systems design [Panchal 2015].

While fundamental research on using crowdsourcing for design is very limited, there has been significant effort on modelling research contests in the literature on research contracts, and procurement of innovation. This has resulted in a well-developed theory of contests [Corchón 2007]. The theory of contests can provide insights for designing good crowdsourcing contests. The literature on design contests has not yet been sufficiently leveraged within the design community. We believe that this is due to a combination of different factors: (i) crowdsourcing is a relatively new phenomenon in design, (ii) the literature on research contests is focused on issues that have not been at the core of design research, and (iii) the nature of research processes is different from the nature of the design processes.

We have two goals in this paper. The first goal is to establish the relevance of the contest models to engineering design.

We discuss the characteristics of design contests that are similar to research contests, and the characteristics that are unique. We show that models of research contests can serve as a starting point for understanding how to leverage crowds for engineering design. The second goal is to critically evaluate the assumptions and recommendations from the models, and their applicability in the design context. Based on the critical analysis, we identify open research issues that need to be addressed for utilizing contest models within design.

The paper is structured as follows. In Section 2, we provide an overview of game theoretic models of contests. The specific focus is on two types of contests: fixed-prize tournaments and auctions. In Section 3, we discuss a set of representative models, and the insights provided by these models for designing crowdsourcing contests. In Section 4, we analyse the comparative use of auctions and contests within engineering design. Finally, the limitations of the models and the open research issues are discussed.

2. Game-theoretic models of contests and their relevance to engineering design

The use of crowdsourcing contests within different parts of the design process was recently analysed by Panchal [2015]. The author argues that there are different types of initiatives that can be used in engineering design (e.g., contests, open calls, micro-tasks, etc.). Design contests can be designed in many different ways, such as (i) single stage vs. multistage tournament, (ii) open entry vs. restricted entry vs. entry fee, (iii) fixed prize vs. performance based prize vs. auctions, (iv) winner-takes-all vs. multiple prizes vs. auction-style tournaments. Additionally, there are many different criteria with which these initiatives can be evaluated. Examples of these criteria include the solution quality, the number of contributors, the amount of effort invested by the contestants, the quality of teams formed, the overall cost of running the contest, the probability of getting a good solution, and the cost of filtering good solutions.

In the rest of the paper, we focus on one of these decisions – deciding whether to conduct a fixed prize tournament or an auction. *In fixed-prize tournaments*, the winner's prize is fixed before the start of the tournament. Generally, the prize is fixed by the sponsor to restrict his/her expenditure. The advantages of fixed prize tournaments are that they are simple to implement and effective for sponsors with limited information about the problem [Fullerton and McAfee 1999]. On the other hand, *in contests with auctions*, each bidder submits his/her best quality with a bid of the amount to be paid if the design is selected. The sponsor evaluates qualities and corresponding bids from different contestants, and decides the winner. The advantage of auctions over fixed prize tournaments is that auctions reduce the sponsor's burden of determining the right prize amount before the contest [Fullerton et al. 2002]. Additionally, the bidding process provides an additional medium through which the contestants compete with each other.

The effects of auctions and fixed prize tournaments on the performance metrics can be analysed using game-theoretic models of contests. The analysis starts with identifying two types of players, the sponsor and contestants. The sponsor declares the problem to the contestants and notifies them of the type of contest (fixed-prize vs. auctions). Both the sponsor and the contestants are assumed to maximize their own expected payoffs. The payoff of each contestant i is dependent on the prize amount (Π_i), the probability of winning the prize (f_i), and the costs incurred (ψ_i). The probability of winning is dependent on the quality of their own submission (x_i), and the quality of submissions from other contestants. The cost is dependent on factors such as the nature of the problem and the number of experiments carried out. For contestant i, given the prize (Π_i), the expected payoff is $E_C = \Pi_i . f_i(x_i) - \psi_i$. After the contestants have submitted their solutions, the sponsor evaluates the submissions and chooses the winning entry that maximizes his/her payoff (E_s).

2.1 Auctions vs. fixed prize tournaments

The specific differences between the models of auctions and fixed prize tournaments are due to the different payment structures. The prize ($\Pi_i = P$) for the winner in a fixed-prize tournament is decided at the start of the tournament, and is known to all contestants. The winner, here, is the contestant with the best quality. In auctions, contestants privately submit bids ($\Pi_i = p_i$) along with their own best quality (x_i). Therefore, the winner in auctions is decided based on the maximization of sponsor's payoff E_s, which is dependent on both quality and price.

In auctions, the sponsor is interested in better quality and cheaper price. The sponsor's payoff function is generally simplified by assuming quality to be the sponsor's *monetary valuation* of a solution. This allows direct numerical comparison between quality and price while evaluating the payoff, E_s. Therefore, the payoff takes a simple form, referred to as *surplus* $(s = x - p)$. The sponsor is assumed to decide the winner after evaluating each contestant's surplus, $x_i - p_i$. The surplus is, therefore, the decision variable for the sponsor and the scoring function for contestants.

Many articles exist in economics and management science literature that have focused on studying the details of auctions and contests [Taylor 1995], [Fullerton et al. 2002], [Che and Gale 2003], [Schottner 2008] in the context of research contests. These models evaluate the best strategy for the participants in equilibrium, and predict the expected surplus from the participants. The insights from the models indicate that the best design of the initiative depends on the design problem and the associated tasks. Terwiesch and Xu [2008] have shown, for example, that design problems with well-defined goals with no uncertainty in tasks require the inclusion of skilled contestants in a project. On other hand, problems with no clear specifications, leading to uncertainty require large diversity in contestants.

Since these models have been developed for a research context, it is important to understand the underlying assumptions, and the applicability of these models in the design context. Based on our review of the literature, we found that these models are based on assumptions about the nature of the *process* and the *problem*. Specifically, the process of research is either considered to be sequential or parallel, while the problem can have different levels of uncertainty. In Sections 2.2 and 2.3, we discuss these differences and their implications on using these models in the engineering design process.

2.2 Process: sequential vs. parallel

Some game-theoretic models are based on single-period innovation contests [Che and Gale 2003], [Schottner 2008] while others such as [Taylor 1995], [Fullerton et al. 2002], [Sha et al. 2015] focus on multi-periods contests. In single-period contests, the strategy to come up with a quality depends only on the cost of investment for that period. On the other hand, in multi-period contests, the strategy is also dependent on the outcomes and strategies in the previous periods. The cost function $\psi_i(x)$ in single-period contests is only a function of the quality x resulting from a given period, while in multi-period contests, it is a function of the number of prior periods (labelled as e_i). In multi-period contests, if a cost per period is a constant value, C, the total cost is Ce_i.

These assumptions about the research contests relate to the different types of engineering design processes. As Simon [1996] argues, engineering design can be viewed as a search process where designers search for feasible alternatives, acquire information about them through experimentation, and select the best alternative for the design problem. These search processes can be broadly categorized into *parallel* search and *sequential* search [Loch et al. 2001]. The assumption of independence between searches at different steps relate parallel search to single-period contests, while the dependence of searches on previous steps relate sequential search to multi-period contests.

In parallel search, the search strategy at each step is independent of one another. It is also referred to as *sampling,* wherein designers randomize the search to explore the design space. This approach is generally employed in problems where (a) the uncertainty associated with the design space is high, (b) the cost associated with search is low, and (c) the time required to complete the search is low. Here, the designers have more flexibility in testing multiple sample points. For example, in user interface design, customers' changing demands for usability require designers to create multiple design alternatives cheaply and quickly.

In sequential search, the information acquired in the previous steps is used to guide the search in the subsequent steps. In such processes, decisions about search in subsequent steps are made based upon learning from previous steps, stopping the search at the solution where the marginal improvement in quality is outweighed by the marginal cost to conduct next search [Powell and Ryzhov 2012]. Also, when the cost associated with a search and the time required are high, sequential search is employed in order to reduce the uncertainty quickly. For example, in product development, once the product specifications are fixed, the design proceeds with the sequence of searches such as concept design, testing, detailed design, manufacturing and further testing, refinement, etc. Each step depends upon the information gained in the previous step.

2.3 Problem: deterministic vs. stochastic

The game theoretic models of contests use assumed quality functions (x_i) or cost functions $(\psi_i(x))$ to relate the cost of investment to the quality output. Such relation can be deterministic or stochastic. In deterministic form, the quality output is a deterministic function of number of periods e_i [Sheremeta et al. 2012], [Sha et al. 2015] or cost $\psi_i(x)$ [Che and Gale 2003], [Schottner 2008]. This case assumes a complete control over the quality output. In stochastic form, on other hand, the quality output is a cumulative distribution of the quality, $F_i(x)$ [Taylor 1995], [Fullerton et al. 2002]. This case, therefore, assumes uncertainty in the quality output.

Such distinction of quality control relates to the nature of the design problem. In design scenarios, if a designer puts effort for searches, he/she can arrive at the solution deterministically or with uncertainty. For example, consider a towing tank experiment to identify the hydrodynamic performance of an ocean vessel as a function of the Reynolds number. The designer performs a series of experiments to find the resistance of the vessel for various towing speeds or Reynolds number. The "quality" or smoothness of this resistance variation depends on the number of experiments conducted. Each experiment is associated with a pre-determined cost or effort level. Such class of experiments is labelled as *deterministic*. In another experiment where the designer is trying to attain a new variety of steel that meets the requirement of the vessel. The designer has limited prior information on the type of material properties (or "quality") that may be attained by different searches. Here, a search may be using different carbon content or annealing temperature. This class of experiments can be referred to as *stochastic*. Here, the output from investing a certain level of effort is not a deterministic quality, rather a probabilistic distribution.

With this analysis of relevance between game-theoretic models and engineering design, we discuss the details of some models in the following section.

3. Specific models, insights, and their application within engineering design

We start with a simple classification of the models (Figure 1) with the two categories of design processes – sequential and parallel, and the types of contests as the other dimension – fixed prize and auctions.

3.1 Sequential search – fixed prize

This category includes the problems whose design process is viewed as sequential search, and are solved using fixed-prize tournament. Relevant models in this category are Taylor [1995] and Sha et al. [2015]. These models assume that participants undertake research in periods. Research at each period is assumed to have a constant cost, C.

Taylor [1995] analyses tournaments with a fixed maximum period T. The model assumes at least two contestants ($N = 2$) who have to pay an entry fee (E) to participate. At each period, contestants derive the quality probabilistically according the cumulative distribution function $F(x)$. All the contestants have same distribution $F(x)$, i.e., they are symmetric. P, E, N, T and C are assumed to be common knowledge. However, contestant's quality of a solution is private between the sponsor and the contestant, and is unobservable by other contestants.

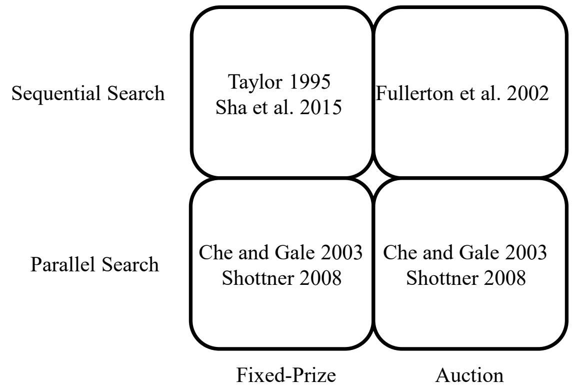

Figure 1. Categorization of models

Under these assumptions, Taylor determines the best strategies for the contestants, including, whether to enter the game and when to stop search. Taylor claims that each contestant decides the next strategy based on the number of contestants and value of its current best quality, x. For a general case of $T \geq 2$, the decision about whether to take an additional period, or not, is based on the net expected improvement in payoff by an additional period. The expected improvement for contestant i is $\Delta_i(x) = P\int_x^b [\Pi_i(y) - \Pi_i(x)]dF(y) - C$, where F is defined on $[0,b]$, $\Pi_i(y)$ is the cumulative distribution of the best quality offered by any of the i's rivals. The contestant stops at the quality (z_i) when the net expected improvement of payoff is zero. This is referred to as *Z-stop strategy*, $\Delta_i(z_i) = 0$.

Sha et al. [2015] assume that the quality achieved at specific period is a function of the number of previous periods. Two choices considered for such function are linear ($x_i = \alpha e_i$) and exponential ($x_i = \alpha \exp(\beta e_i)$). This model assumes two symmetric contestants with the same functional form for the quality. In equilibrium, both contestants choose the optimal number of periods in order to maximize both contestants' expected payoffs. This is done by applying first-order optimality condition on contestants' payoff functions (E_C) with respect to the corresponding previous number of periods.

In summary, Taylor provides the optimal quality (*z-stop*) the sponsor can expect from a particular contestant in fixed-prize tournament in terms of the *z-stop strategy.* Sha et al. [2015], with quality as a function of number of periods, propose the optimal number of periods contestants should take to maximize their payoffs. The optimal quality in equilibrium can then be inferred from a quality-period relation from this model.

3.2 Sequential search - auctions

In this type of scenario, bidders perform research in steps, and at the end of pre-defined number of periods they submit bid prices in addition to the best solution. The relevant model in this section is by Fullerton et al. [2002]. Fullerton et al. extend Taylor's model for the case of auctions. The assumptions and equilibrium characterized in this model are same as in Taylor's model. The expected quality outcome z_i of contestant i from an auction is characterized by the z-stop strategy, $\Delta_i(z_i) = \int_{z_i}^b [p_i(y)\Pi_i(y) - p_i(z_i)\Pi_i(z_i)]dF(y) - C = 0$, where $p_i(y)$ is the equilibrium bidding price function of quality y. This function is transformed from standard first-price, independent-private values auction in *auction theory.* If $\Phi(x; z_i, T)$ represents the cumulative distribution of contestant i's best quality at the end of period T, and if all N contestants are assumed to be symmetric in their quality distribution, the equilibrium bid function is, $p_i(x) = \dfrac{\int_0^x [\Phi(y)]^{N-1} dy}{[\Phi(x)]^{N-1}}$ [McAfee and McMillan 1987].

Fullerton et al. show that when the equilibrium bid $p_i(x)$ is monotonically increasing in quality, the expected cost of the prize in auction is strictly less than the cost of the prize required to elicit the same effort in fixed-prize tournament.

3.3 Parallel search – fixed-prize tournament

The models of parallel search with fixed prize include Che and Gale [2003] and Schottner [2008]. These models consider a single-period innovation with complete control over quality. The models assume that the expected quality increases with contestant's investment. For instance, if a designer invests multiple times to come up with a best quality, the quality output at each draw will be independent of the results of previous draws, and only depend on how much investment is made for that draw.

The model by Che and Gale [2003] assumes a deterministic relation between the investment cost $\psi_i(x)$ and the quality x_i. The quality x_i is unobservable to other contestants. The cost function, however, is assumed to be common knowledge among all players. The model characterizes a mixed-equilibrium to predict the contestants' behaviour for two participants. Given that the contestants are symmetric and have knowledge about the other contestant's cost function, both receive zero expected payoff ($E_C = 0$) at equilibrium. Their quality distributions at equilibrium are, therefore, $F_i(x) = \frac{\psi_i(x)}{P}$. The sponsor can expect the quality outcome x_{exp} to be an expectation of quality with respect to distributions $F_1(x)$ and $F_2(x)$. In order to evaluate the optimal fixed-prize P_{opt} for the tournament, the expected payoff of the sponsor E_s is maximized by applying the first-order optimality condition, $E_s = \max_{(Popt)}\left(x_{exp} - P\right)F_{-i}\left(x_{exp}\right)$, where x_{exp} is a function of P, and $F_{-i}(x)$ represents the probability of winning for contestant i, which depends upon the quality distribution of the other contestant ($-i$). The expected surplus from the fixed-prize tournament is, therefore, $s_{exp} = x_{exp} - P_{opt}$.

Schottner [2008] models quality as a combination of a deterministic component (referred to as investment strategy) and a random variation. The investment cost $\psi_i(x)$ of coming up with a given quality is a deterministic function of investment strategy. The investment cost, in contrast to Che and Gale [2003], is assumed to be private information. But the output quality of each contestant (x_i) is considered to be common knowledge among all the contestants. The equilibrium in this model for a fixed-prize tournament is characterized for two contestants based on the difference between their quality outputs. Schottner [2008] argues that the large uncertainty in this difference, due to a large variation in a random component of the quality, can be economically disadvantageous for the sponsor. Since the quality x_i is common knowledge, the large difference in qualities may elicit high bid prices in auction. Therefore, under these assumptions, fixed-prize tournament is a better choice for the sponsor.

In summary, for parallel search process in engineering design, Che and Gale [2003] define the optimal quality output the sponsor can expect, and the optimal fixed prize for the tournament. In addition, Schottner [2008] suggests that the sponsor should prefer fixed-prize tournament in design problems with high uncertainty.

3.4 Parallel search - auctions

The models such as Che and Gale [2003] and Schottner [2008] are also applicable in parallel search process with auctions. These models analyse auctions to answer the questions such as: what is an optimal bidding strategy for contestants? how much payoff do bidders achieve? what is the expected surplus from an auction? and do auctions perform better than fixed-prize tournaments?

The assumptions in Che and Gale [2003] model for auctions are the same as the assumptions discussed in Section 4.3 for fixed-prize tournaments. The model characterizes the mixed-equilibrium strategies for two symmetric contestants in an auction who receive zero expected payoffs in equilibrium. This model assumes a complete control over choosing a quality. In equilibrium, the contestants' strategy is to choose the optimal quality x_{opt} that minimizes the other contestant's surplus distribution $G_{-i}(s)$ at equilibrium,

$G_{-i}(s) = min_{(x_{opt})}[\frac{\psi_i(x)}{x-s}]$. The expected surplus, thus, is an expectation with respect to $G_1(s_1)$ and $G_2(s_2)$, i.e., $s_{\exp} = E(s \mid s = s_i \; and \; s_i > s_{-i})$. The model results in the optimal bidding price function from contestant i at equilibrium as: $p_i = \frac{\psi_i(x)}{\psi_i^{'}(x)}$.

It can be inferred from Che and Gale's model that if $\psi_i(x)$ is of form x^n / k, where n is an integer greater than 1, and k is a positive constant, an auction always provides better surplus than a fixed-prize tournament. $\psi_i(x)$, here, satisfies the conditions of the model by Che and Gale [2003], i.e., it is a convex, increasing function, is zero at zero quality, and crosses a threshold quality x_{thd} such that $\psi_i(x_{thd}) > x_{thd}$. Schottner [2008], as discussed in Section 4.3, suggests that a fixed-prize tournament dominates a first-price auction if quality is common knowledge and uncertainty in quality submissions is high.

4. Analysis of models for the context of engineering design

4.1 Examples of applications in engineering design

Innovation contest models from economics and management science literature are based on assumptions about contest settings, problem specification, behaviour of participants in equilibrium, and exchange of information. The models discussed in Section 4 are summarized in Table 1. These models provide design-specific insights in terms of the expected solution output from the contest and the cost of conducting a contest. Consider an example of the *FANG* challenge by DARPA [2010], which involved an online contest to design an amphibious transport vehicle. The fixed prize $1 million was awarded to the winning design. Although participants, non-traditional defence engineers, in such contests require certain level of expertise, the uncertainty is high because of their unfamiliarity with the sponsor's (DARPA) military requirement of a more-integrated vehicle. This ideation-based project, thus, can be categorised as *fixed-prize parallel search contest*. The quality of submissions was private. Assuming the validity of the model by Che and Gale [2003] for the FANG challenge, optimal quality from this contest would be $x_{\exp}$ given in Section 3.3. Also, the model suggests that having an auction instead of fixed-prize in *FANG* challenge would have been profitable. If, however, the designs were observable to others before bidding in auction, Schottner's model suggests that fixed-prize would be better than auctions.

Topcoder.com, also employs fixed-prize tournaments for challenges for software development. The challenges, submitted by IT companies (sponsor) are open to participants who are required to possess sufficient programming skills. With well-defined problem statements and skills requirements, the contests fall under the category of *fixed-prize sequential search contests.* Also, the quality of solution is almost a deterministic function of how much effort the coder puts in the development. As the quality is a private variable, Taylor's model applies in this case with quality distribution $F(x)$ varying in a small range to satisfy near deterministic trend. Taylor model predicts the expected quality (*z-stop*) from these contests according *z-stop strategy*. Fullerton et al. [2002] model suggests that having an auction instead of fixed-prize is profitable for IT companies. If, however, the quality was observable by others, the optimal quality output from the contest and the optimal effort required from the participants is given by Sha et al. [2015].

Table 1. Model assumptions and results

Model	Design Process	Payment Structure	Quality	Cost	Equilibrium	Results
Taylor [1995]	Sequential	Fixed-prize	Stochastic; prior distribution assumed; Private	Constant value per try; Common Knowledge	Bidder stops at specific try given by Z-*stop strategy*	Expected quality (*z-stop*) from fixed-prize contest

Fullerton et al. [2002]	Sequential	Fixed-prize and Auction	Stochastic; prior distribution assumed; Private	Constant value per try; Common Knowledge	Bidder stops at specific try given by *Z-stop strategy*	Auction costs lesser to achieve the same expected *z-stop*
Che and Gale [2003]	Parallel	Fixed-Prize and Auction	Deterministic; Full control over quality using invest-ment; Private	Deterministic function of quality; Common Knowledge	Symmetric bidders offer the same surplus (two bidders)	Expected surplus higher in auction than fixed-prize
Schottner [2008]	Parallel	Fixed-Prize and Auction	Deterministic and Stocha-stic parts; Deterministic component dependent upon investment; Common Knowledge	Deterministic function of quality + constant cost for a contest; Private	For small quality difference, bidders (two) offer the same surplus; For large difference, higher quality gives higher surplus	For significant difference between qualities, fixed-prize preferred than auction
Sha et al. [2015]	Sequential	Fixed-Prize	Deterministic; Quality is a function of effort (number of tries); Common Knowledge	Constant value per try; Common Knowledge	Bidders (two) get maximum payoff; first order optimality condition on payoff wrt effort	Number of tries by bidders, and corresponding quality output in equilibrium

4.2 Research gaps

The economic behaviour of contest models is largely unclear in real-world scenarios. The difficulty in understanding this relationship, first, arises due the in-appropriateness of their assumptions about quality and cost in design scenarios. Second, behaviour of participants in actual contests may not be rational, as assumed while analysing the equilibrium behaviour. Specific research gaps include:

1. Deterministic relation between the solution quality and investment in research, assumed in many contest models, is generally unknown in engineering design.
2. The degree of influence of design expertise on the contest outcomes is not extensively modelled in the literature. The models such as [Terwiesch and Xu 2008] propose to tackle expertise. However, these models decouple the cost from expertise. Based on expertise and experience of the designer, and accessibility to technological infrastructure, the cost incurred during product development will be different for two different contestants.
3. The search process, in most design problems, is a combination of parallel and sequential unlike the rigid assumptions in the contest models. In the initial design stages, uncertainty involved is high; hence, exploration and parallel search strategy dominates. In the later stages, with a reasonable understanding of the design space, the sequential strategy dominates. Models such as [Loch et al. 2001], [Erat and Krishnan 2013] analyse this combination, but its effects in contest design remains unexplored.
4. The effect of design space on the solution quality is not accounted for in the contest models. The question of where to look for a solution is largely unanswered. Rather, these models focus on whether to look for a solution.

5. Closing comments

Crowdsourcing contests have been employed by many organizations (e.g., Innocentive.com, DARPA 2010, Challenges.gov, and Local Motors) to solve engineering problems. In this paper, the focus is on two mechanisms frequently used in engineering contests, fixed-prize tournaments and auctions. There is a lack of knowledge in the design community on how the two contests perform in terms of the quality outcome, cost of prize, participation, etc. Most contests are conducted as fixed-prize to restrict the expenses. This requires deeper knowledge of the field on the part of the solution seeker to decide the prize amount. Also, different economic models [Fullerton et al. 2002], [Che and Gale 2003] suggest that auctions reduce the expenses of conducting a contest.

In this paper, we categorize engineering problems based on their characteristics such as design process and uncertainty in achieving a solution to transform them into noted contest models. Further, we arrive at guidelines for organising tournaments to solve these problems. The guidelines are broadly categorized in three steps:

1. Match the problem to one of the models. The assumptions listed in Table 1 facilitate the matching of the problem with a suitable model.
2. Estimate the expected quality of the output and the expected cost of prizes using insights from the model. Once the contest model is identified for a problem, its results provide insights into questions such as which payment structure to use, what quality or surplus to expect from the contest, what time restraints to impose on the participants, etc.
3. Choose the optimal contest (fixed-prize tournament or auction) for the given problem. Two examples discussed in Section 4.1 elaborate this step on choosing an appropriate contest.

Apart from quality, cost and payment, many other aspects of contests such as entry fees, number of participants, and multiple-prizes need to be analysed from a design point of view to evaluate their applicability in engineering design. In addition, other mechanisms such as patent races, matching between the sponsor and designers etc. that influence innovations need to be studied from design perspective to include them in mainstream innovation activities.

Acknowledgments

The authors gratefully acknowledge the financial support from the US National Science Foundation (NSF) through grants 1265622 and 1400050.

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