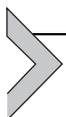


Managing Conflicts Among Decision Makers in Multiobjective Design and Operations*

V.M. Zavala

Argonne National Laboratory, Argonne, IL, United States



INTRODUCTION

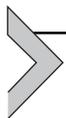
Almost any decision-making activity involves multiple decision makers (stakeholders). For instance, in the design of a process system, stakeholders must trade off myriad economic, environmental, and safety metrics (objectives) [1]. The stakeholders likely will disagree on which metrics should be used and on how they should be prioritized. If disagreements are not systematically managed, they can leave a subset of stakeholders strongly dissatisfied, a situation that can ultimately delay consensus reaching and lead to arbitrary decisions.

The most popular approach for dealing with multiple objectives in a decision-making process is to compute a Pareto front and then use *expert* knowledge to make a final decision by choosing a suitable point along the front. This approach has two important disadvantages: (1) it is ambiguous in that it assumes that a single decision maker (expert) makes the final decision (which is often not the case), and (2) the complexity of forming the Pareto front is exponential in the number of objectives, and choosing a particular point along the front is cumbersome in multiple dimensions. Another approach commonly used in multiobjective decision making is to give equal priority to all objectives. This approach is equivalent to picking a specific point along the Pareto front and therefore is also ambiguous. Moreover, the approach is unreliable because, depending on the shape of the Pareto front, a slight modification of the weights can yield drastically different solutions [2]. In other words, this approach does not capture the shape of the Pareto front and thus might neglect solutions that yield high returns for one objective with few sacrifices for others. Another popular approach in multiobjective decision making is to prioritize objectives, as proposed in [3]. This approach, however, also assumes that a single decision maker is involved in creating the priority hierarchy, and consequently it is ambiguous.

*Argonne National Laboratory, operated by UChicago Argonne, LLC, under Contract No. DE-AC02-06CH11357 with the US Department of Energy.

Ambiguity can be mitigated by considering the opinion of multiple stakeholders when choosing a suitable Pareto solution (compromise solution). An interesting multistakeholder approach was presented in [4]. Here the authors assume that stakeholders are polled to provide *priority rules* to be followed. From these rules, a unique set of weights that satisfy such rules is computed. A disadvantage of this approach is that it can yield situations in which no unique feasible weights can be obtained that satisfy all the stakeholders' rules. In addition, this approach does not provide insights into the level of dissatisfaction of the stakeholders with a given compromise decision.

In this work we present an optimization framework that systematically quantifies and mitigates dissatisfactions among stakeholders. The idea consists of factoring the opinion of the multiple stakeholders in the form of weights (instead of rules). Consequently, compared with the approach presented in [4], the proposed framework provides more flexibility. The framework is an extension of the robust optimization approach proposed in [5] in which a compromise decision is obtained by minimizing the maximum dissatisfaction among stakeholders. A key advantage of the robust approach is that it provides a measured stakeholder disagreement. In addition, it does not require the computation of a Pareto front and can thus be used to address problems with many objectives and stakeholders. We generalize this approach by considering average and conditional-value-at-risk (CVaR) metrics. This generalization enables us to shape the distributions of the stakeholder dissatisfactions and capture the statistics of the stakeholder population more effectively. We argue that this feature is advantageous in certain applications. In addition, generalizing the robust approach using CVaR and average metrics enables us to provide utopia-tracking interpretations of the different metrics in a common setting. The proposed approach provides a systematic procedure to inform decision makers about the influence of their opinions on the final decision and can help decision makers *reassess* their priorities and thus resolve and quantify the *cost of conflict*. Examples are presented to illustrate the concepts.



APPROACH

Consider a set of objectives functions $\mathcal{O} := \{1 \dots O\}$ and the corresponding objective function vector $\mathbf{f}(x)^T = [f_1(x), f_2(x), \dots, f_O(x)]^T$. Consider also a set of stakeholders $\mathcal{S} := \{1 \dots S\}$ and the case in which each stakeholder $s \in \mathcal{S}$ prioritizes the objectives according to a weight vector $w_s \in \mathbb{R}^{\mathcal{O}}$. We define the elements of the weight vectors as $w_{s,i}$, $i \in \mathcal{O}$, and we assume that the weight vectors satisfy $\sum_{i \in \mathcal{O}} w_{s,i} = 1$, $i \in \mathcal{O}$.

A key observation that we make is that, if the stakeholder population is finite, we can interpret the weight vectors as samples from a probability distribution with finite support. In other words, the weight vectors can be interpreted as samples from the population of stakeholders. Each stakeholder $s \in \mathcal{S}$ seeks to solve its individual weighted optimization problem

$$\min_x \mathbf{w}_s^T \mathbf{f}(x) = \sum_{i \in \mathcal{O}} w_{s,i} f_i(x) \quad [7.1a]$$

$$\text{s.t. } g(x) \leq 0. \quad [7.1b]$$

Here the constraint vector $g(x)$ includes operational constraints and/or system models. The solution of problem [7.1] will yield an optimal solution x_s^* and a weighted cost for stakeholder s that we denote as $\mathbf{w}_s^T \mathbf{f}_s^* := \mathbf{w}_s^T \mathbf{f}(x_s^*)$. This weighted cost is ideal, or utopian, in the sense that it assumes that stakeholder s does not have to compromise with the rest of the stakeholders. When compromise is needed, as is often the case, we define the dissatisfaction of stakeholder s at an arbitrary compromise decision x as $d_s(x) := \mathbf{w}_s^T (\mathbf{f}(x) - \mathbf{f}_s^*)$. Note that from optimality of x_s^* and associated weighted cost $\mathbf{w}_s^T \mathbf{f}_s^*$, we have that $d_s(x) \geq 0$ for all x and for all $s \in \mathcal{S}$.

Consider now that two arbitrary decisions \bar{x}, x yield $d_s(\bar{x}) < d_s(x)$. Thus stakeholder s will be more satisfied under decision \bar{x} than under decision x . Because of disagreement, however, another stakeholder s' might be less satisfied under decision \bar{x} than under decision x (i.e., $d_{s'}(\bar{x}) > d_{s'}(x)$). We thus have that, given a compromise decision x , we can measure the disagreement among stakeholders by using a measure of the dissatisfactions $d_s(x)$, $s \in \mathcal{S}$. Note that the ideal case with no disagreement at decision x occurs only when $d_s(x) = 0$ for all $s \in \mathcal{S}$. In the presence of disagreements among stakeholders, however, this situation cannot occur.

Our objective is thus to find a compromise decision x that minimizes a measure of the dissatisfactions $d_s(x)$, $s \in \mathcal{S}$. We can think of this problem as one of shaping the distribution of the dissatisfactions. For convenience, we define the vector of dissatisfactions $\mathbf{d}(x)^T := [d_1(x), d_2(x), \dots, d_S(x)]^T$.

The most straightforward alternative for managing disagreements consists of minimizing the average dissatisfaction among the stakeholders. This is done by solving the problem

$$\min_x \frac{1}{|\mathcal{S}|} \sum_{s \in \mathcal{S}} \mathbf{w}_s^T (\mathbf{f}(x) - \mathbf{f}_s^*) \quad [7.2a]$$

$$\text{s.t. } g(x) \leq 0. \quad [7.2b]$$

Because $d_s(x) \geq 0$ for all $s \in \mathcal{S}$ and x , we have that problem [7.2] is also equivalent to

$$\min_x \frac{1}{|\mathcal{S}|} \|\mathbf{d}(x)\|_1 = \frac{1}{|\mathcal{S}|} \sum_{s \in \mathcal{S}} d_s(x) \quad [7.3a]$$

$$\text{s.t. } g(x) \leq 0. \quad [7.3b]$$

In other words, the solution of problem [7.2] can be interpreted as a compromise solution relative to a utopia point given by the collection of the ideal stakeholder weighted costs $\mathbf{w}_s^T \mathbf{f}_s^*$. This definition of utopia point is not to be confused with the traditional definition used in multiobjective optimization [6].

Another way to address disagreement consists of minimizing the worst (largest) dissatisfaction among the stakeholders. This is done by solving the robust optimization problem

$$\min_x \max_{s \in \mathcal{S}} \{ \mathbf{w}_s^T (\mathbf{f}(x) - \mathbf{f}_s^*) \} \quad [7.4a]$$

$$\text{s.t. } g(x) \leq 0. \quad [7.4b]$$

This formulation was proposed in [5]. It is well known that the min–max problem [7.4] can be reformulated as

$$\min_x \eta \quad [7.5a]$$

$$\text{s.t. } \mathbf{w}_s^T (\mathbf{f}(x) - \mathbf{f}_s^*) \leq \eta, s \in \mathcal{S} \quad [7.5b]$$

$$g(x) \leq 0. \quad [7.5c]$$

The optimal value of η is the worst dissatisfaction. Because $d_s(x) \geq 0$, a solution x of problem [7.4] also solves the problem

$$\min_x \frac{1}{|\mathcal{S}|} \|\mathbf{d}(x)\|_\infty = \frac{1}{|\mathcal{S}|} \max_{s \in \mathcal{S}} \{d_s(x)\} \quad [7.6a]$$

$$\text{s.t. } g(x) \leq 0. \quad [7.6b]$$

Because we can assume that the stakeholders' polls are obtained from a finite distribution, we can measure the disagreement by using a risk metric such as CVaR. To this end we solve the following problem:

$$\min_x \text{CVaR}_\alpha [\mathbf{w}_s^T (\mathbf{f}(x) - \mathbf{f}_s^*)] \quad [7.7a]$$

$$\text{s.t. } g(x) \leq 0. \quad [7.7b]$$

Here $\alpha \in [0, 1]$ is the probability level. This problem can be reformulated as [7]

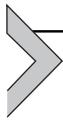
$$\min_{x, \nu, \phi_s} \frac{1}{|\mathcal{S}|} \sum_{s \in \mathcal{S}} \left(\frac{1}{1 - \alpha} \phi_s + \nu \right) \quad [7.8a]$$

$$\text{s.t. } \mathbf{w}_s^T (\mathbf{f}(x) - \mathbf{f}_s^*) - \nu \leq \phi_s, s \in \mathcal{S} \quad [7.8b]$$

$$\phi_s \geq 0, s \in \mathcal{S} \quad [7.8c]$$

$$g(x) \leq 0. \quad [7.8d]$$

This approach penalizes the large dissatisfactions in the $(1 - \alpha)$ tail of the distribution. One can show that the CVaR solution converges to the robust solution as $\alpha \rightarrow 1$ and to the average solution as $\alpha \rightarrow 0$ [8]. Consequently, the CVaR solution covers the spectrum of solutions between the average and robust solutions.



ILLUSTRATIVE EXAMPLES

In this section we present examples to demonstrate the applicability of the presented concepts.

Generation Expansion

Consider a decision-making setting in which a community (stakeholders) needs to decide among three technologies (denoted as I, II, and III) for power generation. In doing so, the community must satisfy a given demand while trading off three objectives: minimize electricity cost (denoted as C), minimize carbon emissions (denoted as E), and minimize land use (denoted as L). Table 7.1 lists the coefficients for cost, emissions, and land use for the three technologies.

The coefficients are adimensional and are used only to represent relative magnitudes of different technologies. Technology I has high emissions, low cost, and high land use (relative to the others). Technology II has low emissions, high cost, and medium land use. Technology III has medium emissions, medium cost, and low

Table 7.1 Emissions, Cost, and Land Use for Each Technology

Technology	E	C	L
I	100	10	100
II	50	50	50
III	75	50	25

land use. The weighted multiobjective optimization problem can be formulated as follows:

$$\min w_C C + w_E E + w_L L \quad [7.9a]$$

$$\text{s.t. } C = \gamma_I C_I + \gamma_{II} C_{II} + \gamma_{III} C_{III} \quad [7.9b]$$

$$E = \gamma_I E_I + \gamma_{II} E_{II} + \gamma_{III} E_{III} \quad [7.9c]$$

$$L = \gamma_I L_I + \gamma_{II} L_{II} + \gamma_{III} L_{III} \quad [7.9d]$$

$$D = \gamma_I P_I + \gamma_{II} P_{II} + \gamma_{III} P_{III} \quad [7.9e]$$

$$\gamma_I, \gamma_{II}, \gamma_{III} \in \{0, 1\}. \quad [7.9f]$$

Here, γ_I , γ_{II} , and γ_{III} denote the decisions to install technology I, II, or III, respectively. Symbol D denotes the electricity demand, and P_I , P_{II} , and P_{III} denote the power supplied by each technology. For simplicity we assume that $P_I = P_{II} = P_{III} = 10$, and we set $D = 10$. Note that the demand constraint [7.9e] implies that only one technology must be installed. All the objectives (C, E, L) are normalized by their best and worst possible values (these can be obtained from Table 7.1) so as to lie in the range [0,1].

In Table 7.2 we present the average and worst-case solutions under four different polls from 100 stakeholders. We assume that the polls are designed in such a way that the stakeholders express four different opinions: (1) their only priority is emissions, (2) their only priority is cost, (3) their only priority is land use, and (4) all three objectives are equally important. In a first poll we have {50%, 50%, 0%, 0%}, in a second poll we have

Table 7.2 Compromise Solutions Under Different Polls

Poll	Strategy	Compromise Solution
{50%,50%,0%,0%}	Average	$\gamma_I; \gamma_{II}$
	Robust	$\gamma_I; \gamma_{II}; \gamma_{III}$
{49%,51%,0%,0%}	Average	γ_I
	Robust	$\gamma_I; \gamma_{II}; \gamma_{III}$
{25%,25%,25%,25%}	Average	γ_{II}
	Robust	$\gamma_I; \gamma_{II}; \gamma_{III}$
{0%,0%,0%,100%}	Average	γ_{II}
	Robust	γ_{II}

{49%, 51%, 0%, 0%}, in a third poll we have {25%, 25%, 25%, 25%}, and in a fourth poll we have {0%, 0%, 0%, 100%}. The first poll indicates that 50% of stakeholders give full priority to minimize emissions and 50% give full priority to minimize cost. In the second poll the number of stakeholders giving full priority to minimize cost dominates by 1% the number of stakeholders giving full priority to minimize emissions. In the third poll 25% of the stakeholders give full priority to emissions, 25% give full priority to cost, 25% give full priority to land use, and 25% give equal priority to all objectives. The fourth poll corresponds to the special case in which all stakeholders give equal priority to minimize all objectives. In other words, in the fourth poll we have perfect agreement among stakeholders.

From the first three polls we can see that the robust strategy achieves the same worst-case dissatisfaction for all technologies. In other words, the three technologies are optimal in the sense that they minimize the worst-case dissatisfaction. With perfect agreement (fourth poll), on the other hand, technology II is optimal, and the worst-case dissatisfaction is zero. From the first poll we can see that the average strategy predicts that technologies I and II are equally optimal. This result is expected because the number of stakeholders giving priority to emissions and cost is the same so the solutions are indistinguishable. From the second poll we see that technology II is optimal because the number of stakeholders giving priority to cost is larger (by one vote) than the number giving priority to emissions. From the third poll we have the less obvious result that technology II is optimal.

By comparing the results for the robust and average strategies we can obtain some interesting insights. First, we note that in the fourth poll with perfect agreement the robust and the average compromise solutions are equal, as expected. From the rest of the polls, however, the robust solution can be insensitive to the statistics of the polls. While this feature might seem desirable at first sight, it is not likely to be accepted by stakeholders because it implies that their opinions do not influence the solution (even if there is a majority of stakeholders). In fact, in this example, even a poll with a distribution of {1%, 99%, 0%, 0%} will give the same compromise solution under the robust approach. The average approach, on the other hand, does account for the statistics of the stakeholder polls; but it cannot guarantee minimization of the worst dissatisfaction, as the robust approach does.

Energy—Comfort Management in Buildings

One of the objectives of an energy management system is to minimize energy subject to thermal comfort constraints of a population of occupants (stakeholders) [2,9]. Thermal comfort is difficult to enforce because perceptions vary significantly from individual to individual as a result of variations in factors such as metabolic rate (e.g., activity, gender, race, age), building location (e.g., next to air damper, next to

window), and clothing level. To address this disagreement we can poll the occupants about their temperature preferences. Consider the following stakeholder problem in which we seek to minimize energy demand while satisfying the stakeholder j temperature constraint:

$$\min E(T) \tag{7.10a}$$

$$\text{s.t. } T \geq T_j, (\lambda_j). \tag{7.10b}$$

Here $E(\cdot)$ is the building energy that is a function of occupant's j temperature requirement T_j . Clearly, $-\lambda_j = \frac{\partial E}{\partial T_j}$ and $-\lambda_j > 0$ if the objective and the comfort constraint are in conflict. Consequently, λ_j can be interpreted as a comfort price. We can thus formulate the weighted multiobjective problem

$$\min w_{j,1}E(T) + w_{j,2}T, \tag{7.11}$$

with $w_{j,1} := \frac{1}{1+\lambda_j}$ and $w_{j,2} := \frac{\lambda_j}{1+\lambda_j}$. For simplicity we assume that energy is a quadratic function of the difference between the building temperature and the ambient temperature,

$$E(T) := (T - T_{\text{amb}})^2 \tag{7.12}$$

and we set the ambient temperature to 35°C .

We consider a poll of temperature preferences for $S = 1000$ occupants in a building. The average preference is 22°C , the minimum temperature preference is 15°C , and the maximum preference is 29°C . All temperatures are below ambient temperature, and we thus simulate a situation in which energy is used for cooling. Thus if comfort is not a concern, the energy required will be zero, and the building will be set at ambient temperature. This also implies that, as T_j is increased, the comfort price λ_j will decrease and will be zero at T_{amb} . We thus have that the weight $w_{j,2}$ will tend to zero and $w_{j,1}$, reflecting the fact that a larger T_j implies a lower priority on comfort. Consequently, polling temperature preferences can be interpreted as polling priorities of energy and comfort among occupants.

In Fig. 7.1 we present the corresponding comfort weights $w_T(w_{j,2})$ for the occupants. In Fig. 7.2 we present the Pareto curve of temperature against energy demand. Each point along the front is obtained by solving problem [7.10] for each stakeholder s . Note that these points represent the ideal (nonachievable) situation in which each stakeholder can reach the desired temperature preference without having to compromise with the rest of the stakeholders. In the figure we also present the solution of different compromise decisions. The vertical line indicates the solution in which the stakeholders compromise naively by averaging their temperature

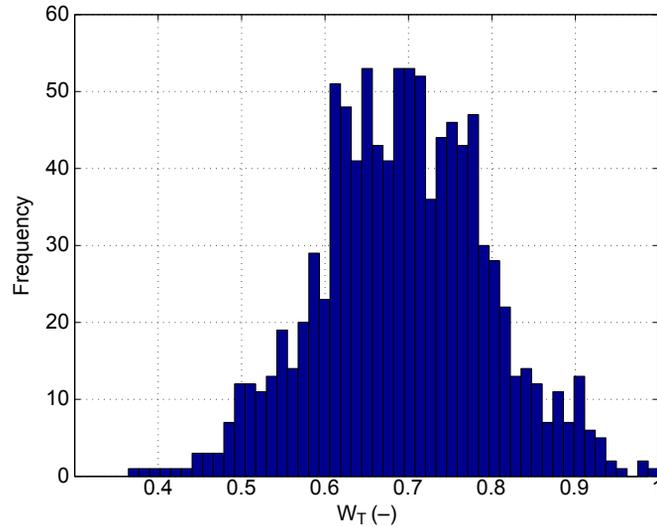


Figure 7.1 Occupants' weights on temperature.

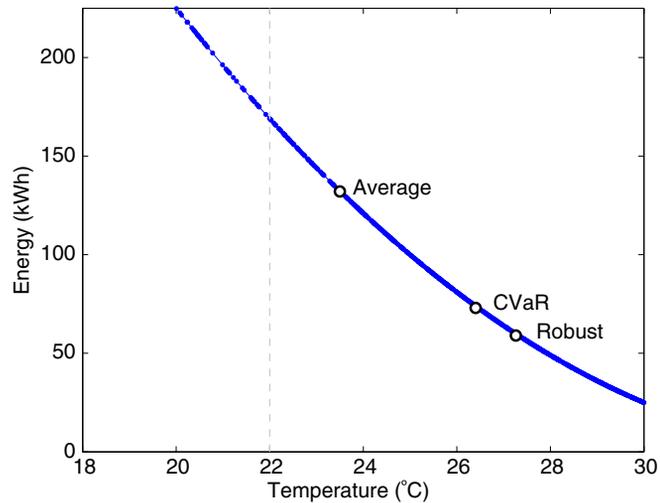


Figure 7.2 Pareto front and compromise decisions. Vertical line is naive approach. CVaR, conditional-value-at-risk.

preferences (22°C). This solution corresponds to solving the energy minimization problem

$$\min E(T) \quad [7.13a]$$

$$\text{s.t. } T \geq \frac{1}{|S|} \sum_{j \in S} T_j. \quad [7.13b]$$

Note that this naive approach does not capture energy in the stakeholders' opinions. The black dot next to the naive solution represents the solution obtained by compromising based on the minimization of the average dissatisfaction given by [7.2]. The solutions obtained by averaging preferences and minimizing the average dissatisfaction do not coincide. The reason is that averaging temperatures is not equivalent to averaging dissatisfactions: dissatisfactions factor in energy and not only temperature. The black dots at the end of the Pareto front represent the decision obtained by minimizing CVaR for $\alpha = 95\%$ given by [7.7] and the decision obtained by minimizing the worst dissatisfaction among the stakeholders given by [7.4]. Note that the compromise decisions move toward the maximum temperature preference (warmer building) as robustness is increased. Consequently, the CVaR and robust approaches yield much lower energy demands than do the naive and average approaches. From the naive approach perspective (without factoring in energy in the opinions) this result is counterintuitive because one would expect that at a higher temperature more people would be dissatisfied. From a dissatisfaction perspective, however, a colder building yields much larger dissatisfactions.

These results illustrate how a more systematic management of stakeholder opinions can yield more efficient (and nonintuitive) solutions. In Fig. 7.3 we present histograms

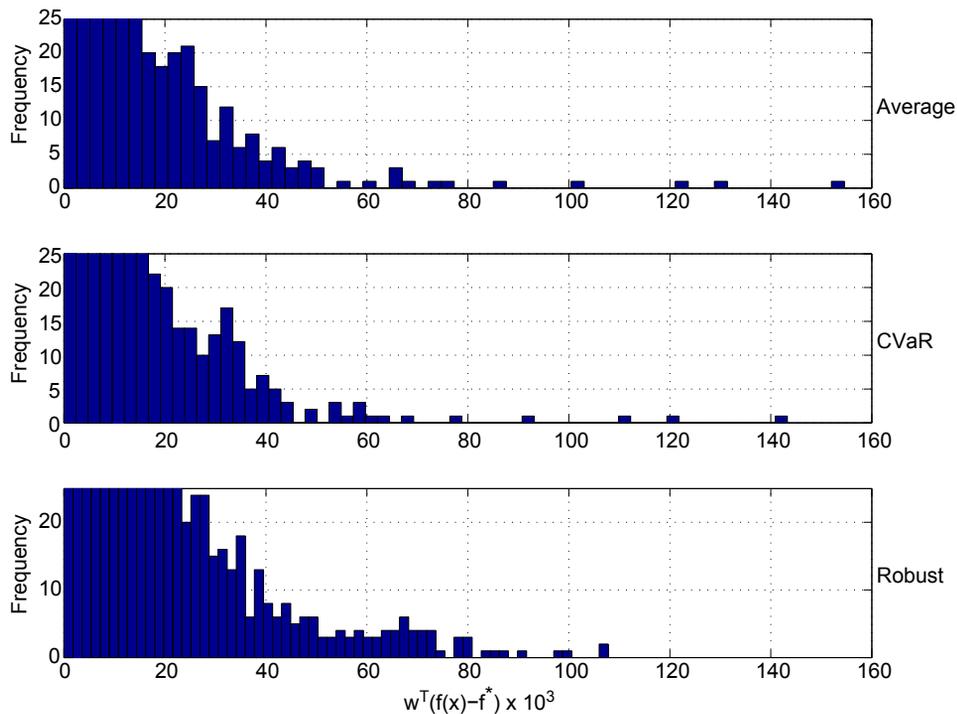
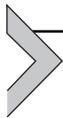


Figure 7.3 Dissatisfaction of stakeholders under different compromise decisions. CVaR, conditional-value-at-risk.

for the dissatisfactions of all the stakeholders. In the top graph we present the dissatisfactions when the stakeholders compromise by minimizing the average dissatisfaction. Note the pronounced tail of large dissatisfactions. In the middle graph we present the dissatisfactions when the stakeholders compromise by minimizing CVaR, and in the lower graph we present the dissatisfactions when the stakeholders compromise by minimizing the worst dissatisfaction. Note that the tail of the distribution of dissatisfactions is reduced by CVaR and that the robust approach reduces the tail further by penalizing the largest dissatisfaction. We can thus see that in this application the robust approach provides important benefits compared with the average approach.

Arguably, the need to choose among average, CVaR, and worst-case metrics in the proposed approach introduces some ambiguity in the decision-making process in that the stakeholders must also agree that such a metric is the appropriate one. The level of ambiguity, however, is significantly reduced compared with standard multiobjective approaches that assume a single decision maker. Moreover, the proposed approach has the additional advantage that it can manage many opinions and objective functions in a systematic manner.



CONCLUSIONS

We have presented a framework to manage conflicts among multiple decision makers. The framework enables the computation of compromise solutions in the presence of many objectives without having to form a Pareto front. The framework also provides a systematic procedure to manage conflicts by using quantifiable metrics of disagreement among stakeholders.

We highlight that the framework proposed can manage objective functions in either deterministic or stochastic settings. For instance, one can trade off mean profit and profit variance. Our framework, however, does not account for situations in which stakeholders can change their preferences based on possible scenarios, as discussed in [6]. We will extend our framework to consider this possibility in future work. It is also necessary to consider formulations under which the stakeholders provide their preferences not only in terms of weights but also in terms of goals. This will give rise to interesting goal-oriented multiobjective formulations. We are also interested in understanding under what conditions the CVaR compromise solution gives a Pareto solution. This is motivated from the fact that the average and robust metrics have utopia-tracking interpretations (under different norms). We will look for a similar definition in the CVaR case.

ACKNOWLEDGMENTS

This material was based upon work supported by the US Department of Energy, under contract no. DE AC02-06CH11357. The author thanks Sanjay Mehrotra for suggesting the building energy management example.

REFERENCES

- [1] Ruiz-Mercado GJ, Smith RL, Gonzalez MA. Sustainability indicators for chemical processes, I: Taxonomy. *Ind Eng Chem Res* 2012;51(5):2309–28.
- [2] Zavala VM. Real-time resolution of conflicting objectives in building energy management: an utopia-tracking approach. In: *Proceedings of the 5th National Conference of IBPSA-USA*; 2012. p. 1–6.
- [3] Mendoza GA, Prabhu R. Multiple criteria decision-making approaches to assessing forest sustainability using criteria and indicators: a case study. *For Ecol Manag* 2000;131(1):107–26.
- [4] Smith RL, Ruiz-Mercado GJ. A method for decision making using sustainability indicators. *Clean Technol Environ Policy* 2014;16(4):749–55.
- [5] Hu J, Mehrotra S. Robust and stochastically weighted multiobjective optimization models and reformulations. *Oper Res* 2012;60(4):936–53.
- [6] Zavala VM, Flores-Tlacuahuac A. Stability of multiobjective predictive control: a utopia-tracking approach. *Automatica* 2012;48(10):2627–32.
- [7] Tyrrell Rockafellar R, Uryasev S. Optimization of conditional value-at-risk. *J Risk* 2000;2:21–42.
- [8] Tyrrell Rockafellar R, Uryasev S. Conditional value-at-risk for general loss distributions. *J Bank Finance* 2002;26(7):1443–71.
- [9] Morales-Valdez P, Flores-Tlacuahuac A, Zavala VM. Analyzing the effects of comfort relaxation on energy demand flexibility of buildings: a multiobjective optimization approach. *Energy Build* 2014;85(0):416–26.