Chapter 50
Robust Design Optimization of Steel Moment Resisting Frame Under Ground Motion Uncertainty

Zhifeng Liu, Sez Atamturktur, and Hsein Juang

Abstract In the design of a steel moment resisting frame, uncertainties may arise from a variety of sources, such as ground motion, mass, and damping ratio, etc., that may cause variation in seismic demand and capacity. These uncertainties need to be taken into account to ensure the desired margin of safety for required performance objectives. FEMA 350, a reliability based design guideline, can be employed to mitigate safety concerns by satisfying minimum confidence level requirements for performance objectives. However, in these existing design codes, variation in seismic demand is not explicitly considered in the design process. According to the FEMA 350 procedure, seismic demand is calculated with a suite of seismic records, considering ground motion variability, while only median demand is used in the subsequent calculation of demand to the capacity ratio and confidence level. In this paper, variation of seismic demand due to ground motion variability is considered explicitly as a *robustness measure*, and the mean value of seismic demand is treated as a *safety measure*. A Robust Design Optimization of steel moment resisting frame methodology is proposed, which is featured as a multi-objective optimization problem with the variation of seismic demand, mean value of seismic demand and cost as three objectives. In the optimization problem, optimal steel section sizes are sought to minimize these three conflicting objectives. The proposed methodology is then demonstrated through a multi-story multi-bay steel moment resisting frame design and solved with a Non-dominated Sorting Genetic Algorithm-II. With three competing objectives, the proposed methodology provides a set of designs in the form of a Pareto Front, which is robust, safe and economical. Furthermore a uniformity drift ratio requirement is proposed to ensure efficient designs.

Keywords Multi-objective optimization • NSGA-II • Pareto front • Modal pushover analysis (MPA) • Demand and capacity factor design (DCFD)

50.1 Introduction

Traditionally, designing a steel moment resisting frame (henceforth referred to as the steel frame) is a trial and error process, seeking designs that are both safe and economical. Safety is ensured by complying with reliability based design standards (e.g., [1, 2, 7], etc.), while cost is evaluated considering the initial construction cost. A design is then selected from several code-compliant candidate designs, based on the cost and other considerations. Due to limitations on design budgets, only a few candidate designs are typically compared, thus the design chosen is likely suboptimal in the sense of cost and/or safety.

To address this economical concern, steel frame design optimization has been studied extensively in past years. These studies have been formulated as either single objective optimization or multi-objective optimization problems. In single objective optimization, an optimization algorithm is employed in place of a trial and error design process, and the entire solution space is explored in search of the most economical design with building codes and other project requirements treated as constraints [12, 25]. When other criteria, such as the number of steel sections [14], and the confidence level of the designs performance are considered as objectives simultaneously with cost, the design optimization process becomes a multi-objective optimization problem ([8, 13, 20, 21]).

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A review of literature conveys that robustness of seismic demand to uncertainty is rarely considered in either traditional or optimization-based steel frame design. Due to inherent uncertainty in the construction and operational conditions of the structure, seismic demand may deviate from the expected value. Without considering the robustness of seismic demand to uncertainty, one may reach a design that has a large sensitivity to uncertainty and thus, large variation in performance. Herein, robustness to uncertainty is considered in the context of 'Robust Design' as originally proposed by Taguchi [24]. In this paper, a new steel moment resisting frame design optimization approach named *robust design optimization* is proposed, utilizing robust design concept originally developed and widely used in quality engineering [19, 24]. In the proposed approach, maximum inter-story drift is considered as seismic demand measure, and the ground motion variability is considered as the source of uncertainty. The mean value of maximum inter-story drift is treated as the safety criterion; the standard deviation of the maximum inter-story drift is treated as the robustness criterion, and material weight is treated to represent the cost of the design, and these three criterions are optimized simultaneously. Therefore, the proposed approach leads to a multi-objective optimization problem resulting in a set of competing designs that are economical, safe and robust.

50.2 Robust Design

Robust design, which has been successfully used in industrial and manufacturing engineering to produce high quality products and processes, aims to make a product or response of a system insensitive to (or robust against) "hard-to-control" input parameters (called "noise factors"), by carefully adjusting "easy-to-control" input parameters (called "design parameters" or "control factors"). Two kinds of approaches are most widely used in robust design: (i) the Taguchi method and its variants [19, 24], and (ii) the Robust Design Optimization method [18].

The Taguchi method is fundamentally an experimental design approach, in which orthogonal array is employed to assign design parameters and noise factors [19]. Analysis of mean is performed to characterize design parameters into four categories: (i) design parameters affecting mean and variance of the response, (ii) design parameters affecting variance only, (iii) design parameters affecting mean only, and (iv) design parameters affecting cost only. Design parameters of the first two categories are adjusted to reduce variance; the third category is adjusted to move the mean value of the response to the target value and the last category is adjusted to reduce cost [19]. Though easy to implement, the following limitations of the Taguchi method have made it the subject of criticism ([3, 16]): (i) design parameters cannot always be grouped into four distinct categories; and (ii) due to the inherent experimental nature of the design, only a select few designs may be evaluated and compared, prohibiting a thorough exploration of the design space.

With the development of computational capabilities and progress in the optimization techniques, Robust Design Optimization (RDO) has gained popularity [3]. Three goals of robust design, which are (i) reducing variance in system response, (ii) reducing cost and (iii) adjusting mean value of system response to the target, lead naturally to a multi-objective optimization problem. In some cases, the target value for the mean is specific; in others, the mean value is either maximized or minimized. RDO is advantageous as it can explore the entire solution space to find the most optimum design and straightforwardly evaluate highly nonlinear problems. In the present study, RDO is adopted for the performance based seismic design of steel moment resisting frames.

50.3 Performance Based Seismic Design

In traditional seismic design, preventing collapse and fatality is the only goal, however, in performance based design, structural performance is divided into several levels each corresponding to a seismic hazard level. FEMA 350 supplies a probability based guideline for performance based design of steel frames, in which the ground motion variability and the uncertainty in the structural analysis are considered explicitly [7]. FEMA 350 considers two performance levels, immediate occupancy (IO) and collapse prevention (CP), corresponding to 50% probability of exceedance in 50 years and 2% probability of exceedance in 50 years, respectively. In FEMA 350, performance objective is satisfied probabilistically in that IO performance level has an annual frequency of being exceeded less than 1/100, while CP performance level has an annual frequency of being exceeded less than 1/2500.

Analogous to LRFD design format, in FEMA 350, the performance objectives are satisfied by demand and capacity factor design (DCFD) method [11], instead of direct calculation of the annual frequency of being exceeded. However, in FEMA 350, only median seismic demand is involved in computation of demand to capacity ratio and the subsequent calculation of confidence level, while variation of seismic demand is not considered. In this paper, the authors apply the principles of

robust design optimization to performance based design of steel moment resisting frames. Seismic demand, system response of interest, is represented with maximum inter-story drift, which reflects both local and global stability, as well as P-Δ effects [22]. The mean value of maximum inter-story drift, μ_{drift} is considered as the safety measure and the standard deviation of maximum inter-story drift, σ_{drift} is considered as the robustness measure. For the cost measure, initial construction cost, represented by steel material weight is adopted [14]. Ground motion variability, a significant contributor to seismic demand variation [6], is treated as the noise factor. The [1] requirements and FEMA 350 acceptance criteria are implemented as design constraints. The performance based robust design optimization of steel moment resisting frame problem is expressed as follows:

$$\text{Find } d \text{ to minimize} : \{W(d), \ \mu_{drift}(d,z), \ \sigma_{drift}(d,z)\}$$

$$\text{Subject to} : \text{AISC-2005 Code Requirements;}$$

$$\text{FEMA350 Acceptance Criteria.}$$

where W is the steel material weight, d is the design parameters (steel section types), z is noise factor (ground motion variability). It should be noted, μ_{drift} and σ_{drift} are calculated under 2% probability of exceedance in 50 years hazard level, since the consequence of exceeding CP performance is more detrimental.

50.4   Methodology: Multi-Objective Optimization

A general multi-objective optimization problem can be expressed as:

$$\text{Minimize} : \mathbf{F}(\mathbf{d}) = [f_1(\mathbf{d}) \ \ f_2(\mathbf{d}) \ \ \dots \ \ f_l(\mathbf{d})]$$

$$\text{Subject to} : g_i(\mathbf{d}) \leq 0 \ \ i = 1, \dots, n \tag{50.1}$$

with f representing a single objective function, and g representing a constraint function. Unlike single objective optimization, the purpose of which is to search for a single best design, multi-objective optimization yields a family of optimum designs. When the objectives are uncooperative (i.e., conflicting), a single design optimum for all objectives does not exist in the solution space, which is represented by an unattainable, imaginary point known as the *utopia point* in Fig. 50.1. There generally exists a set of designs in the solution space (i.e., set $\{F(\mathbf{d}) \mid g_i(\mathbf{d}) \leq 0$ for all i$\}$), which are superior to all other designs, while within this set, no design is superior to another in all criteria. These designs constitute a Pareto optimum set (or Pareto front), as illustrated in Fig. 50.1.

Hence, the Pareto front can be viewed as a set of designs, which dominate all other designs. The *domination relationship* is defined as follows: design B is dominated by design A, if A is superior to B in at least one criteria (i.e., $f_i(d)_A < f_i(d)_B$ for at least one i), and A is not inferior to B in all other criteria (i.e., $f_i(d)_A \leq f_i(d)_B$ for all other i). If one design is not dominated by any other designs, it belongs to the Pareto front. A Pareto front has the following features: (1) Within the Pareto front,
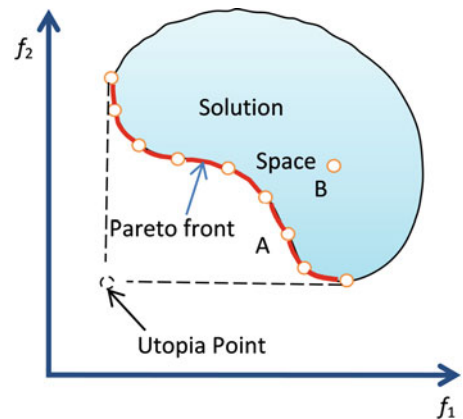

Fig. 50.1 Pareto front in a bi-objective space [9]

no improvement is possible in one objective without worsening other objectives. Thus, the Pareto front represents a trade-off relationship, in which objectives compete with each other. (2) All other designs in the solution space are known as dominated designs, which are dominated by at least one design in the Pareto front. Various optimization methods have been proposed for solving the multi-objective optimization problem, a comprehensive survey of which is provided by Marler and Arora [15].

50.5   Application: Steel Moment Resisting Frame Case

The proposed performance based robust design optimization is illustrated on a four-story three-bay steel moment resisting frame assumed to be located in Los Angles, California (Fig. 50.2). The two-dimensional frame system in N-S direction is employed as illustrative example, with an assumed dead load of 70 psf for the floor and 56 psf for the roof including the weight of slabs. The live load is assumed to be 40 psf for floor levels and 15 psf for roof level, and the external wall load is assumed to be 30 psf for all levels. A572 grade 50 steel is used for all beams and columns. All beams at the same floor level are grouped into the same section type, and the columns of two adjacent floors symmetric with respect to the vertical center line are grouped together. This grouping results in a total of eight section types, i.e., eight design parameters. During optimization, steel sections are selected from the list of commonly used sections in tradition steel moment resisting frame design given in Table 50.1.

Twenty ground motions for both 50%/50 year and 2%/50 year seismic hazard levels developed for the Los Angeles SAC project are used [23]. The ground motions are scaled to match the 50%/50 year and 2%/50 year uniform hazard spectrums through least-square minimization at 0.5, 1, 2 and 4 s. The modal pushover analysis (MPA) procedure proposed by Chopra and Goel [4] is adopted to calculate seismic demand, due to its ability to efficiently yield acceptable accuracy. Structural
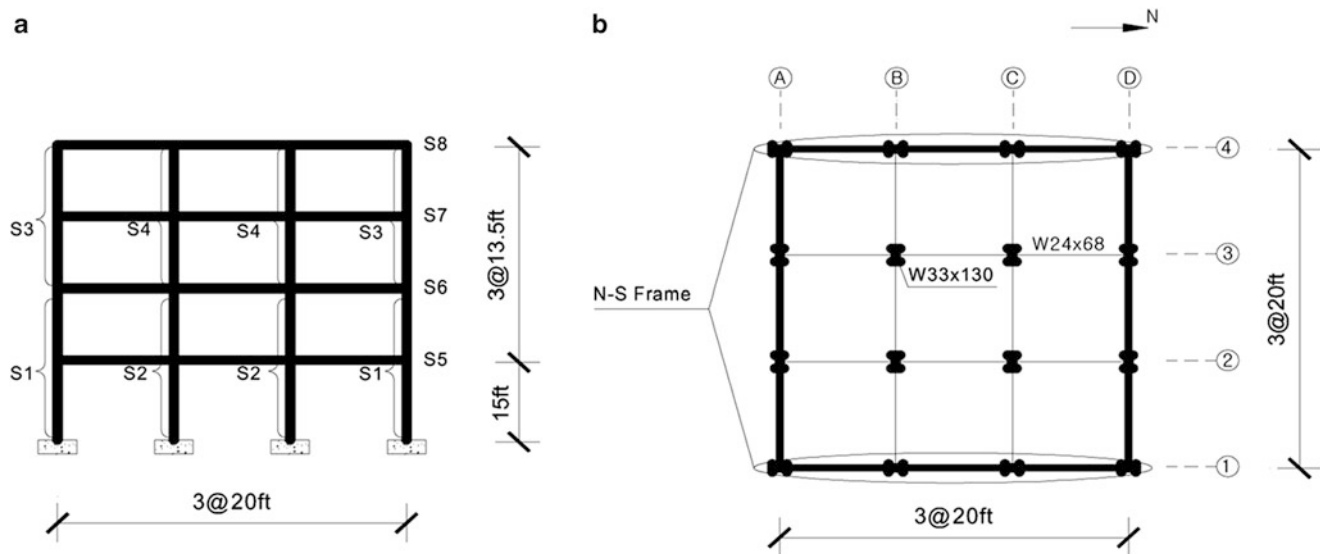

Fig. 50.2 (**a**) Elevation view and (**b**) plan view of the example steel moment resisting frame

Table 50.1 List of columns and beams

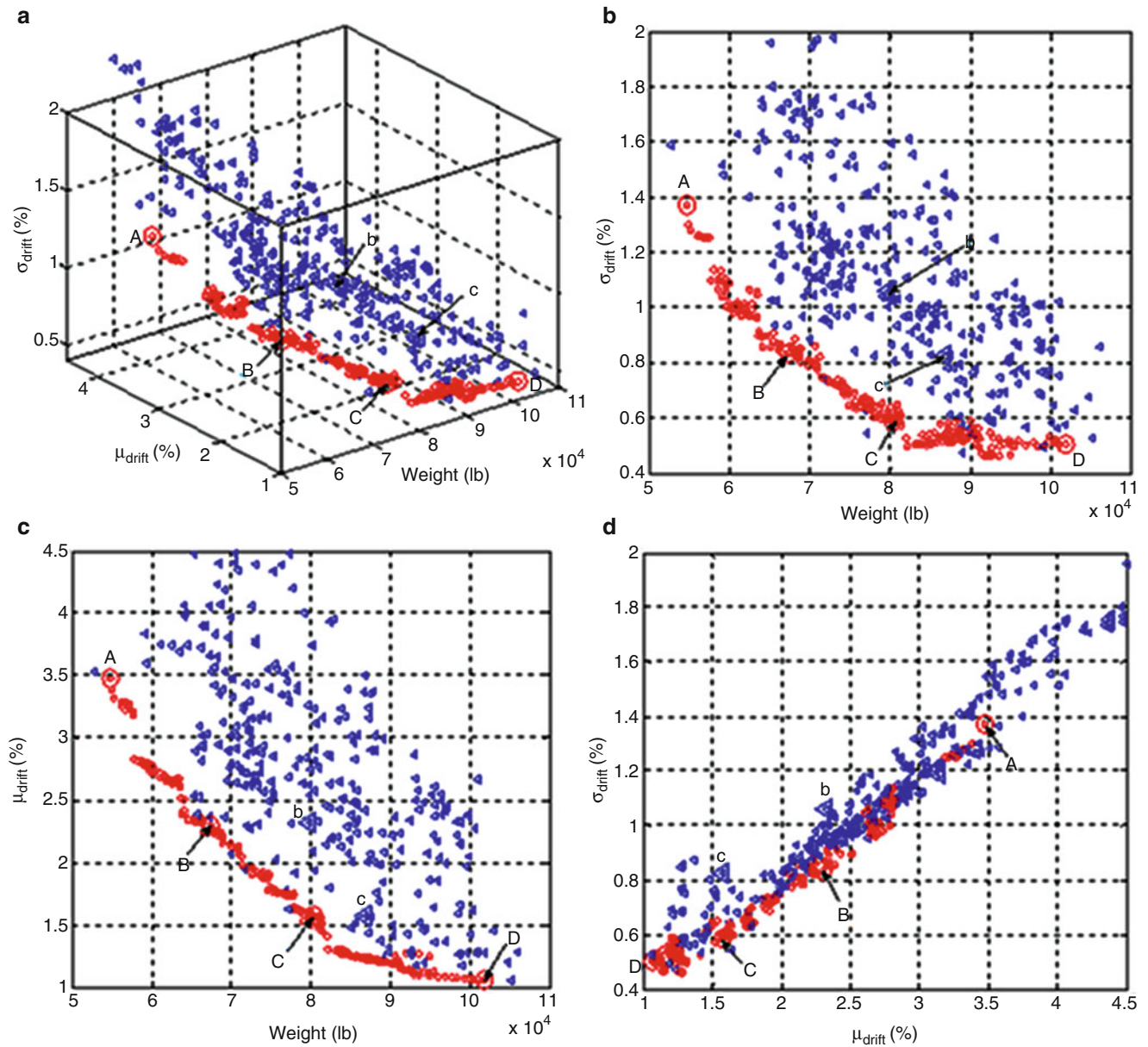| Column		Beam	
W14 × 99	W14 × 211	W24 × 55	W33 × 116
W14 × 109	W14 × 233	W24 × 62	W33 × 130
W14 × 120	W14 × 257	W24 × 68	W33 × 141
W14 × 132	W14 × 283	W24 × 76	W33 × 150
W14 × 145	W14 × 311	W27 × 84	W36 × 135
W14 × 159	W14 × 342	W27 × 94	W36 × 150
W14 × 176	W14 × 370	W27 × 102	W36 × 160
W14 × 193	W14 × 398	W27 × 114	W36 × 170

Fig. 50.3 Pareto Front and dominated designs, 3D an plan view (**a**). 3D view; (**b**) Relation between weight and σ_{drift}; (**c**). Relation between weight and μ_{drift}; (**d**). Relation between μ_{drift} and σ_{drift}.

analysis is performed with open system for earthquake engineering simulation (OpenSEES) [17]. 'nonlinearBeamColumn' element with a strain hardening ratio of 3% is used to simulate a column. The nonlinearity of the beam elements is modeled with Ibarra-Krawinkler (IK) model [10].

The formulated optimization problem is solved through NSGA-II [5] by evaluating 500 designs in each generation with a total number of 50 generations. The converged solution, i.e., the acquired Pareto front of the last generation, is shown in Fig. 50.3. For comparison purposes, Fig. 50.3 also depicts the feasible designs of generation 1. Since no designs belong to Pareto front in generation 1, they are termed as 'Dominated Designs' in the figure.

50.6 Discussions

50.6.1 Relation Between μ_{drift} – Cost and σ_{drift} – Cost

The design population of the initial generation and the last generation is illustrated in Fig. 50.3. As the σ_{drift}-Weight (cost) plot (Fig. 50.3) clearly indicates, the Pareto front designs are more robust (smaller σ_{drift}) than dominated designs for identical cost. For identical robustness (σ_{drift}), Pareto front designs are more economical than dominated designs. From the μ_{drift}-Weight (cost) plot (Fig. 50.3), the Pareto front designs are observed to exhibit smaller seismic demand (μ_{drift}) compared to the dominated designs for identical cost, while for designs with identical seismic demand (μ_{drift}), the Pareto front designs are more economical than the dominated designs.

In general, for given cost, both μ_{drift} and σ_{drift} can be greatly optimized, i.e., with steel weight as 8000 lb, σ_{drift} can be improved from the worst case of 1.6% in dominated designs to the best case of less than 0.6% in Pareto front, and μ_{drift} can be improved from the worst case of 3.7% in dominated design to the best case of around 1.5% in Pareto front. For identical μ_{drift} or σ_{drift} , cost of the designs can also be greatly optimized, i.e., with μ_{drift} as 2%, steel weight can be reduced from the worst case of 100,000 lb in dominated designs to the best case of 7,100 lb in Pareto front; with σ_{drift} as 1%, steel weight can be reduced from the worst case as 100,000 lb in dominated designs to the best case as 6,000 lb in Pareto front.

In the first generation, designs are randomly generated and the code-compliant designs are selected as feasible designs–similar to the trial and error process of inexperienced designers. The implication is that though trial and error process can yield code-compliant designs, these designs are far from being optimum. The designs of the first generation can be improved in terms of both robustness (σ_{drift}) and cost as observed from Fig. 50.3 and in terms of both seismic demand (μ_{drift}) and cost as observed from Fig. 50.3.

Six designs are selected for comparison, for which the steel sections and objective function values are listed in Table 50.2. Designs A, B, C and D are selected from the Pareto front, while Designs b and c are dominated designs. Designs A and D are the lightest design and the heaviest design in Pareto front, respectively. Designs A, B, C and D reflect the tradeoff relationship between cost and safety: the design with smaller μ_{drift} inevitably costs more, and the design with less cost inevitably has larger μ_{drift}. With the tradeoff relationship between cost and μ_{drift}, more informed decision making can be achieved.

In single objective optimization, potential changes in safety or robustness due to an increase or decrease of project cost is not supplied. With Pareto Front, however, this information becomes readily available. For instance, comparing designs A and C, with material weight increase from 54792 to 80361 lb (by 46.7%), the μ_{drift} will be reduced from 3.48% to 1.57% (by 54.9%). As a result, the decision maker has control on risk and budget associated with the preferred design. A risk-adverse decision maker may choose a design with smaller μ_{drift} with a higher budget, while a risk-prone decision maker may choose a design with a greater μ_{drift}. A decision maker may also evaluate the necessary budget for a project when using a Pareto front.

Table 50.2 Steel section size and objective values of selected designs

Selected designs		Design A	Design B	Design b	Design C	Design c	Design D
Columns	Storey 1 and 2	W14 × 159	W14 × 159	W14 × 211	W14 × 211	W14 × 283	W14 × 398
		W14 × 193	W14 × 342	W14 × 398	W14 × 398	W14 × 370	W14 × 398
	Storey 3 and 4	W14 × 159	W14 × 159	W14 × 145	W14 × 159	W14 × 99	W14 × 193
		W14 × 193	W14 × 211	W14 × 193	W14 × 283	W14 × 370	W14 × 398
Beams	Storey 1	W24 × 76	W27 × 102	W24 × 68	W33 × 116	W36 × 135	W33 × 130
	Storey 2	W24 × 76	W27 × 102	W36 × 135	W33 × 116	W36 × 160	W33 × 130
	Storey 3	W24 × 55	W24 × 55	W27 × 84	W24 × 76	W24 × 55	W27 × 94
	Storey 4	W24 × 55	W24 × 55	W36 × 160	W24 × 55	W24 × 55	W24 × 55
Weight (lb)		54792	67377	79785	80361	86847	101826
μ_{drift}		3.48	2.30	2.32	1.57	1.57	1.06
σ_{drift}		1.37	0.83	1.06	0.58	0.83	0.50

Fig. 50.4 CDF of inter-story drift of six selected designs
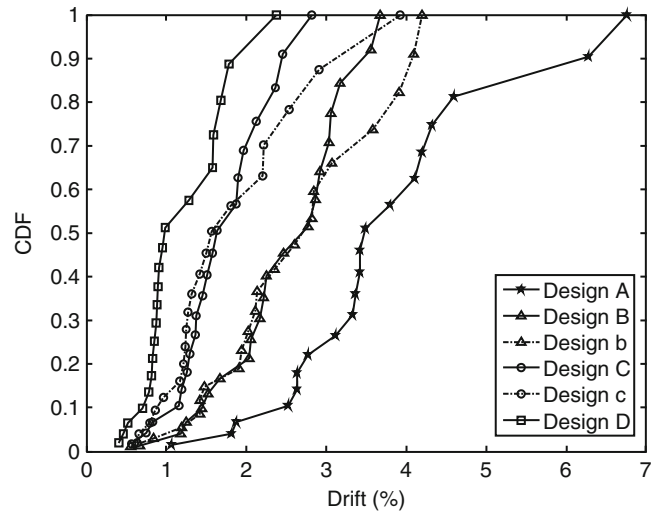
50.6.2   Relation Between μ_{drift} and σ_{drift}

The data from μ_{drift}-σ_{drift} plot (Fig. 50.3d) indicates a positive correlation between μ_{drift} and σ_{drift}, i.e. designs with a larger μ_{drift} also have a larger σ_{drift}.

The cumulative distribution of the six designs is plotted, as shown in Fig. 50.4. Comparing designs A, B, C and D, the probability of not being exceeded increases from design A to D for identical specified μ_{drift}. Though designs B and b have comparable μ_{drift}, design B is safer than design b, as it has a larger probability of not being exceeded for identical inter-story drift (as $\mu_{drift} > 2.7\%$), due to its smaller σ_{drift}. The same relation between design C and design c is also observed. Thus, for identical μ_{drift}, increasing robustness (reducing σ_{drift}) has the benefit of increasing safety (smaller probability of being exceeded).

50.6.3   Uniformity Drift Ratio as a Design Efficiency Indicator

Inter-story drift ratio for all six selected designs are plotted in Fig. 50.6. For each design, the maximum inter-story drift occurs at one or two stories for almost all ground motions, known as weak stories. It is apparent from both Fig. 50.5 that maximum inter-story drift of designs b and c exhibit a much greater variance than designs B and C. Furthermore, variation of inter-story drift between different stories of designs B and C is also smaller than that of designs b and c. That is to say designs B and C exhibit a more uniform distribution of the inter-story drift. Though designs b and c are heavier than designs B and C, they are inferior designs, as the inappropriate proportioning of stiffness and strength make them prone to weak story mechanism failure, i.e., failure due to excessive inter-story drift at one or several stories.

Comparing designs A, B, C and D, the uniformity of the inter-story drift decrease from design D to A. With larger strength, design D would be within its linear range. Whereas design A, as the 'weakest' design, yields even when subjected to low intensity ground motion. After yielding, the stiffness of design A is greatly reduced, thusly sharply increasing the displacement with a slight increase in force or ground motion intensity. The large σ_{drift} of designs b and c is also caused by the weak story. As observed from Fig. 50.5b, the difference of inter-story drift between different stories is not large for low intensity ground motion, while the difference is greatly amplified as ground motion intensity increases after yielding of the first story, resulting in a much larger variation in maximum inter-story drift.

Merely considering maximum inter-story drift is not sufficient to evaluate a design, as story-wise distribution of inter-story drift is not reflected by maximum inter-story drift. Uniformity drift ratio (UDR), defined as ratio of maximum inter-story drift ratio to roof displacement ratio (ratio of roof displacement to building height), can be employed as indicator of inter-story drift uniformity. According to the definition, UDR should be a value larger than unity, while a smaller UDR indicates a more uniform distribution of inter-story drift.

As for identical cost, Pareto front designs exhibit smaller μ_{drift}, and for identical μ_{drift}, Pareto front designs cost less. Thus, Pareto front designs are more efficient than dominated designs. The traditional trial and error based design is likely to result in dominated designs instead of Pareto front designs, as Pareto front designs occupy a small portion of the solution space.

Fig. 50.5 Inter-story drift ratio
results of all ground motions of
six selected designs.
(**a**). Design A; (**b**). Design B and
Design b; (**c**). Design C and
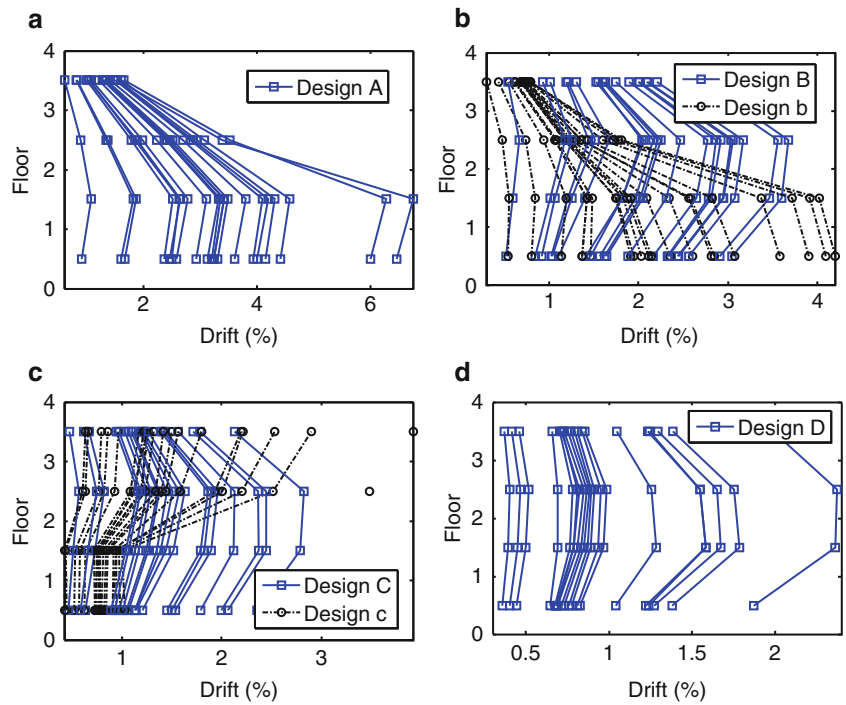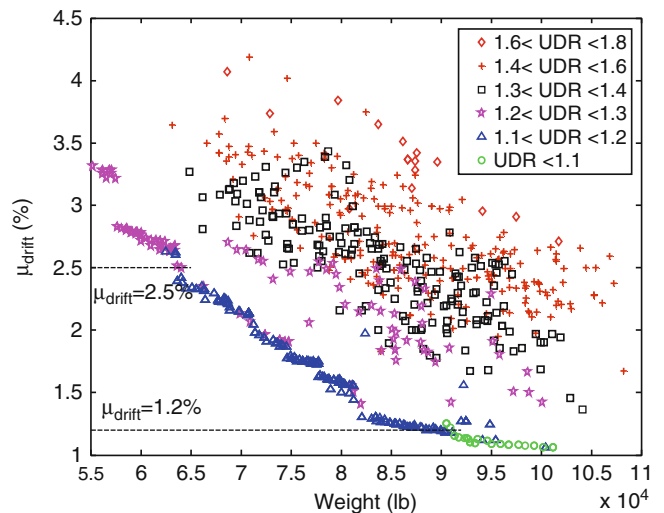Design c; (**d**). Design D

Fig. 50.6 Uniformity drift ratio
distribution for Pareto front
designs and dominated designs

Though Pareto front can be acquired by the multi-objective optimization method, the complex programming of optimization is not practical for practicing engineers, thus simplified method for acquiring Pareto front designs or criteria for ensuring efficiency should be explored. Since inter-story drift is generally positively correlated with strength and stiffness of the corresponding story, thus, UDR is expected to reflect the distribution of strength and stiffness, as a result, it is expected to be a suitable indicator of design efficiency.

To test the applicability of UDR as efficiency indicator, mean value of UDR of the twenty ground motions for Pareto front designs and dominated designs are calculated, as shown in Fig. 50.6. UDR is divided into several ranges. Generally speaking, designs with smaller UDR dominate designs with larger UDR. For every other range of UDR, regions of design are separated clearly, i.e., regions of 1.3<UDR<1.4 and regions of 1.6<UDR<1.8 are not overlapping; the same phenomenon is observed between regions of 1.1<UDR<1.2 and regions of 1.3<UDR<1.4. Since efficient and inefficient designs can be roughly separated with different UDR values, UDR can effectively serve as a design efficiency indicator.

In addition, within Pareto front, designs with larger μ_{drift} generally have larger UDR as well. For μ_{drift} less than 1.2%, all Pareto front designs have a UDR less than 1.1, for μ_{drift} between 1.2% and 2.5%, Pareto front designs have a UDR between 1.1 and 1.2, and for μ_{drift} larger than 2.5%, Pareto front designs have a UDR between 1.2 and 1.3. Designs with larger μ_{drift} are driven to the nonlinear range more severely resulting in larger difference in maximum inter-story drift between stories and in turn, leading to larger UDR. Considering the aforementioned ranges for UDR, whether a design is efficient can be determined by both traditional trial and error based and optimization-based design approaches. It should be noted that the requirement is applicable only for the steel frame considered herein. Whether it can be extrapolated to steel moment resisting frame of different stories, or different structure types need to be verified through more studies. Considering the benefits of appropriately proportioning strength and stiffness, UDR requirement should be considered as a valuable design criterion.

$$\begin{cases} \text{UDR} < 1.1 & \text{for} \quad \mu_{drift} < 1.2\%; \\ \text{UDR} < 1.2 & \text{for} \quad 1.2\% < \mu_{drift} < 2.5\%; \\ \text{UDR} < 1.3 & \text{for} \quad \mu_{drift} > 2.5\%; \end{cases} \tag{50.2}$$

50.7 Conclusion

In this paper, performance based Robust Design Optimization of steel moment resisting frame was proposed, in which cost, mean value of seismic demand and standard deviation of seismic demand are three objectives, ground motion variability is considered as noise factor, and steel section sizes are sought to minimize the objectives. A four-story three-bay steel moment resisting frame is employed as an example to demonstrate the proposed methodology. The following conclusions are drawn:

(1) The methodology proposed can provide a set of competing designs that are economical, safe and robust in the form of a Pareto front, with which structural engineers and stakeholders can make informative tradeoff decisions in a preferred manner.
(2) Pareto front designs are superior to dominated designs in terms of cost, safety and robustness, while traditional trial and error method would most probably result in a dominated design (inefficient design) rather than a Pareto front design (efficient design), as Pareto front designs only occupy a small proportion of all designs in solution space.
(3) For identical mean value of seismic demand, variation of seismic demand can be reduced through adjusting design variables and a safer design can be achieved.
(4) Uniformity drift ratio can be served as design efficiency indicator effectively. Efficient designs generally have smaller uniformity ratio, while inefficient designs generally have larger uniformity ratio. Requirement of uniformity drift ratio conditional on the range of maximum inter-story drift for ensuring efficient designs is suggested. With the suggested requirement enforced, efficient designs can be achieved with the trial and error process without complex optimization.

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