Tensegrity Active Control: Multiobjective Approach

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Abstract: A multiobjective search method is adapted for supporting structural control of an active tensegrity structure. Structural control is carried out by modifying the self-stress state of the structure in order to satisfy a serviceability objective and additional robustness objectives. Control commands are defined as sequences of contractions and elongations of active struts to modify the self-stress state of the structure. A two step multiobjective optimization method involving Pareto filtering with hierarchical selection is implemented to determine control commands. Experimental testing on a full-scale active tensegrity structure demonstrates validity of the method. In most cases, control commands are more robust when identified by a multiobjective optimization method as compared to a single objective one. This robustness leads to better control over successive loading events. Evaluation of multiple objectives provides a more global understanding of tensegrity structure behavior than any single objective. Finally, results reveal opportunities for self-adaptive structures that evolve in unknown environments.

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Introduction

Tensegrities are spatial and lightweight structures composed of compressed struts and tensioned cables. Stability is assured by self-stress. Tensegrities are very flexible: Small loads can induce large displacements. We thus focus on serviceability control in order to provide new opportunities for large structures. Control is carried out by modifying the self-stress state of the structure through contracting or elongating active struts of a full-scale active tensegrity structure built at Ecole Polytechnique Fédérale de Lausanne (EPFL) (Fig. 1). Vertical displacements of three nodes of the top surface edge are measured with displacement sensors.

Previous studies have revealed that many combinations of contractions and elongations of active members can satisfy the serviceability objective of maintaining top surface slope when the structure is subjected to a loading situation (Fest et al. 2004; Domer and Smith 2005). Therefore, this control task could be improved by employing multiple objectives to select the best control set. In structural engineering, researchers have focused mainly on applying multiobjective optimization methods to design tasks (Aguilar Madeira et al. 2005; Maute and Raulli 2004; Park and Koh 2004; Fonseca and Fleming 1998a,b; Kramer and Grierson 1989). Solving a design task involves building a set of good solutions that can be discussed by experts. We propose that a structural control task can be viewed as a multidesign task for multiple loading situations. However, since no expert discussion is possible, automatic single solution selection is needed. This second type of task can be classified as a dynamic multiobjective problem: objective functions, constraints, and associated parameters may be time dependent (Farina et al. 2004).

One of the few examples of a multiobjective optimization method used for control was presented by Hau and Fung (2004). The scope of this numerical study involved controlling the shape of a flexible multilayer beam using a multiobjective genetic algorithm. Objectives are maintaining structural shape and minimizing input voltage for the active system. In the broader civil engineering domain, two control tasks have been supported with a multiobjective optimization method. They are both related to water supply (Baran et al. 2005; Chuntian and Chau 2002). These studies are numerical; no experimental testing was performed. Other control tasks that are supported using multiobjective optimization are far from structural engineering: shop floor scheduling (Hong and Prabhu 2004), multiobjective control for a robotic manipulator (Win and Cheah 2004), a power dispatch task (Zhang and Zhen 2004), portfolio control and optimization (Derigs and Nickel 2004), and ecology (Brouwer and van Ek 2004).

Even for one objective, few studies focus on tensegrity control. Averseng and Crosnier (2004) studied the control of a tensegrity grid where an actuation system is connected to the supports. Other studies of tensegrity control have been conducted mainly through numerical simulation. Kanchanasaratool and Williamson (2002) proposed a dynamic model to study tensegrity feedback shape control. Skelton et al. (2000) concluded that as only small amounts of energy are needed to change the shape of tensegrity structures, they are advantageous for active control. Sultan (1999) proposed a formulation of tensegrity active control and illustrated it with the example of an aircraft motion simulator. Djouadi et al. (1998) described a scheme to control vibrations of tensegrity systems.

Our research involves development of computational control, numeric simulation, and experimental testing. This paper describes how control commands are determined through multiob-

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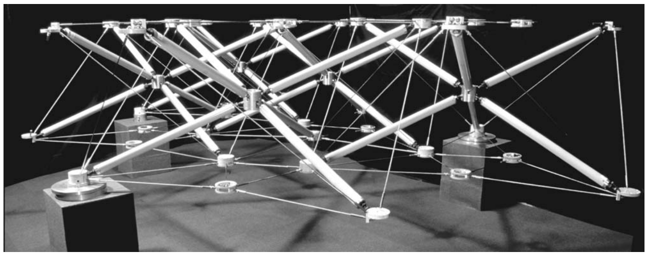

Fig. 1. Five module, 15 m^2 ground projection area of the tensegrity structure built at EPFL

jective optimization. Experimental validation is then carried out on a full scale active tensegrity structure.

Previous Work

Research into active structures has been carried out at EPFL since 1996. Fest (2002) designed and built the laboratory structure and the control system. The topology was proposed by Passera and Pedretti (Lugano, Switzerland) in order to limit the buckling length of compressed members. It contains five modules and covers a surface area of 15 m^2 for a static height of 1.20 m and a mass of 30 kg/m^2. It is composed of 30 struts and 120 tendons. Struts are fiber reinforced polymer tubes of 60 mm diameter and 703 mm^2 cross section. Tendons are stainless steel cables of 6 mm in diameter.

The structure rests on three supports that allow statically determinate support conditions. Struts converge toward a central node where connection is provided by contact compression on a steel ball. In this node, compressive forces always converge to the center of the steel ball. It thus avoids eccentricities that can lead to instability while controlling the structure. The structure is equipped with ten actuators (active members). They are placed in pairs in-line within each of the five modules and make it possible to change length of active struts (Fig. 2). Vertical displacements of three nodes of the top surface edge of the structure are measured with inductive displacement sensors.

The objective of the study was to determine control commands (sequence of contractions and elongations of active struts) that are able to satisfy a serviceability objective: Maintaining the slope of

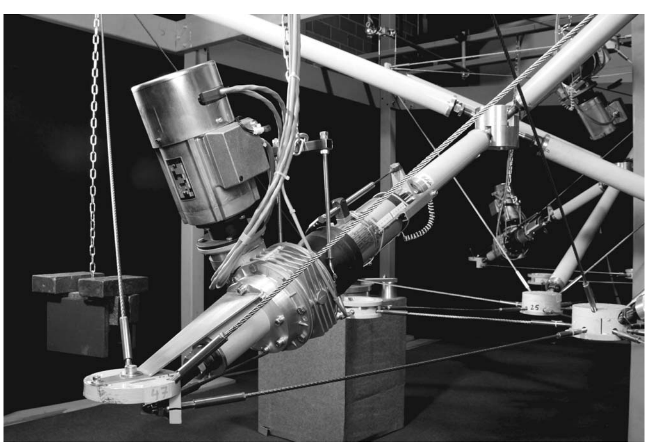

Fig. 2. Actuator: Modify self-stress state by changing length of active members

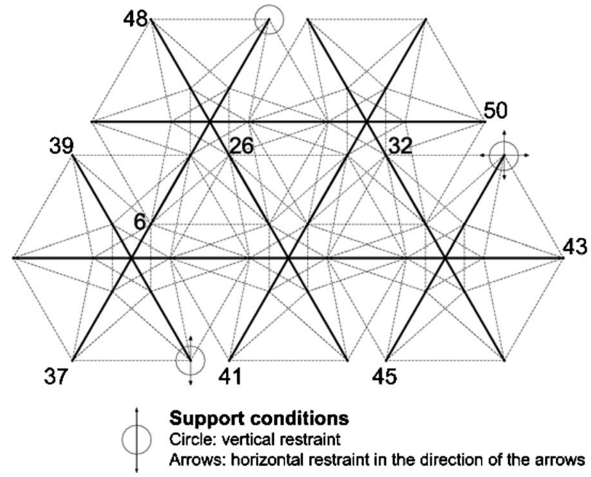

Fig. 3. View of the structure from above, with loaded nodes and support conditions

the top surface of the structure constant when subjected to a load. Slope is determined through vertical displacement measurements at three nodes: 37, 43, and 48 (Fig. 3). This objective is a control criterion that could be useful for structures such as antennas, pedestrian bridges, and temporary roofs. A single objective stochastic search algorithm (PGSL: Probabilistic Global Search Lausanne) was selected as the best stochastic search method to accommodate the combinatorial generate-test process that identifies control commands (Domer et al. 2003). PGSL is a direct search algorithm developed at EPFL (Raphael and Smith 2003).

Although structural calculations that determine structural position using preset strut lengths and loading as input are straightforward with the dynamic relaxation method, the inverse operation of determining strut-length changes to achieve a required behavior of the structure is much more difficult. Closed form methods are unsuccessful because of geometrical nonlinearities, high coupling between elements, coupling between the effect of actuators, and the presence of local minima in the solution space. Once validated, control commands that are found by stochastic search are then applied to the laboratory structure. This study concludes that a stochastic search algorithm and dynamic relaxation have much potential for satisfying a serviceability objective for an active tensegrity structure.

Domer and Smith (2005) studied the capacity of the structure and its control system to learn. A generate-test process was used with stochastic search and case-based reasoning. In order to take advantage of previous experience, altered configurations and corresponding control commands are stored in a case base. When the structure is subjected to a load, the nearby configuration is retrieved from the case base and its control command is adapted to the new task. As cases are added to the case base the average time necessary to identify and adapt a control command decreases (learning). Domer (2003) showed that search time can decrease from approximately 1 h down to a few minutes. As the structure is able to improve performance progressively using past experience, we consider this to be an aspect of intelligence. Clustering cases in the case base was also proposed to speed up the retrieval process. Maintenance of the case-base is crucial to prevent consuming too much time for retrieval. In addition, an artificial neural network was used to model inaccuracies due to joint friction which are not taken into account in the computational model (Domer and Smith 2005). Though correcting the numerical model with neural network accuracy of predictions was enhanced. This study concludes that structural performance could be enhanced by judicious combinations of advanced algorithms. However control commands were identified using a single objective (slope). This approach cannot therefore ensure robustness of the structure and the active control system for subsequent loading and control commands. A multiobjective methodology is reviewed in the following section.

Methodology

Previous studies have revealed that many combinations of contractions and elongations of active struts can satisfy a single serviceability objective to an acceptable degree. This presents an opportunity to enhance control command search through use of additional objectives. Additional objectives should not significantly decrease control command quality with respect to the slope objective. Goals are to increase robustness of both the structure and the active control system in order to carry out multiple control events over service lives. The following four conflicting objectives are used to guide search:

- Slope: Maintain top surface slope of the structure constant when subjected to loading,
- Stroke: Maintain actuator jacks as close as possible to their midpoint,
- Stress: Minimize stress of the most stressed element, and
- Stiffness: Maximize the stiffness of the structure.

The general form of a multiobjective optimization problem can be expressed as follows:

- Minimize objective functions: $\boldsymbol{f}(\boldsymbol{x})$;
- Subject to inequality constraints: $\boldsymbol{g}(\boldsymbol{x}) \leqslant 0$; and
- Equality constraints: $\boldsymbol{h}(\boldsymbol{x})=0$,

where $\boldsymbol{x} \in R^n$; $\boldsymbol{f}(\mathbf{x}) \in \Re^k$; $\boldsymbol{g}(\boldsymbol{x}) \in \Re^m$; and $\boldsymbol{h}(\boldsymbol{x}) \in \Re^p$. Here, n=number of variables; k=number of objective functions; m=number of inequality constraints; and p=number of equality constraints.

Decision variables, objective functions, and constraints of the active tensegrity structure multiobjective control task are expressed as follows in the previous notation.

Decision variables are the position of the ten actuators

$$\boldsymbol{x} = (x_1, x_2, \ldots, x_{10})$$

The four objective functions (slope, stroke, stress, and stiffness) are expressed mathematically in the following: Distance between current slope and initial slope is minimized

$$f_{\text{slope}} = [S(\boldsymbol{x},\boldsymbol{q}) - S^0]^2$$

where S=slope of the top surface of the structure; q=load case set; and S^0=initial slope of the top surface. Slope is formally expressed as follows:

$$S = \left(z_{43} - \frac{z_{37} + z_{48}}{2} \right) \Big/ L$$

where z_{i}=vertical coordinate of node i and L=horizontal length between node 43 and the middle of segment 37–48 (Fig. 3). Slope unit is millimeter/100 meter. The aggregate distance between actuator position and midpoint also has to be minimized

$$f_{\text{stroke}} = \sum_{i=1}^{10} (x_i - x_i^0)^2$$

where x_i^0=midpoint position of the ith actuator.

The stress in the element that is the closest to its limit is minimized

$$f_{\text{stress}} = \max\left(\frac{N(\boldsymbol{x},\boldsymbol{q})_{\text{strut,max}}}{N_{\text{strut,lim}}}, \frac{N(\boldsymbol{x},\boldsymbol{q})_{\text{cable,max}}}{N_{\text{cable,lim}}} \right)$$

where $N_{\text{strut,max}}$=maximum compression force in the struts; $N_{\text{cable,max}}$=maximum tension force in the cables; $N_{\text{strut,lim}}$=−20 kN=limit compression force in struts which corresponds to the half of the buckling load limit; and $N_{\text{strut,lim}}$=8.5 kN=limit tension force in cables which corresponds to the half of the rupture limit.

Maximizing stiffness is equivalent to minimizing compliance indicator

$$f_{\text{stiffness}} = \frac{1}{K}$$

For the purposes of this study, an approximate global stiffness indicator is expressed as follows:

$$K = \frac{Q_{37} + Q_{43} + Q_{48}}{|\Delta S(Q_{37})| + |\Delta S(Q_{43})| + |\Delta S(Q_{48})|}$$

where $\Delta S(Q_i)$=slope variation induced by the vertical downward point load Q_i=1000 N, at node i. As Q_i is expressed in N and $\Delta S(Q_i)$ (mm/100 m), the units of this indicator are Newton/(millimeter/100 m).

Inequality constraints are intended to prevent failure at the compensated slope. Strut buckling and cable rupture have to be avoided. As stability of the structure is provided by self-stress between struts and tendons, and as strut connections are made through contact compression only, tension in struts has to be avoided. Constraints also bound actuator positions. No equality constraints are used for this task. Constraint functions have the following expressions:

$$g_{\text{no\_buckling}} = -\,(N(\boldsymbol{x},\boldsymbol{q})_{\text{strut,max}} - N_{\text{strut,lim}}) \leqslant 0$$

$$g_{\text{no\_tension}} = N(\boldsymbol{x},\boldsymbol{q})_{\text{strut,min}} \leqslant 0$$

$$g_{\text{no\_rupture}} = N(\boldsymbol{x},\boldsymbol{q})_{\text{cable,max}} - N_{\text{cable,lim}} \leqslant 0$$

$$g_{x,\min} = -\,(x_i - x_i^{\min}) \leqslant 0, \quad \forall\, i = 1, \ldots, 10$$

$$g_{x,\max} = x_i - x_i^{\max} \leqslant 0, \quad \forall\, i = 1, \ldots, 10$$

A Pareto filtering approach is employed in order to avoid the use of weight factors. In case of a multiobjective minimization task, a solution x^* is said to be Pareto optimal if there exists no feasible vector of decision variables x which would decrease some objective without causing a simultaneous increase in at least one other objective. This concept results in a set of solutions called the Pareto optimal set. The vectors x^* corresponding to the solutions included in the Pareto optimal set are called nondominated (Pareto 1896).

The multiobjective search method adapted to our tensegrity structure serviceability control task involves building a Pareto optimal solution set and selecting one solution (Fig. 4). The Pareto optimal solution set is identified according to the four objectives and the five constraints described earlier. Solution generation and Pareto filtering are carried out using the ParetoPGSL algorithm. Solutions are generated in order to minimize all objectives. Dominated solutions are rejected. Dominated solutions are defined as solutions that are as good as a Pareto optimal solution

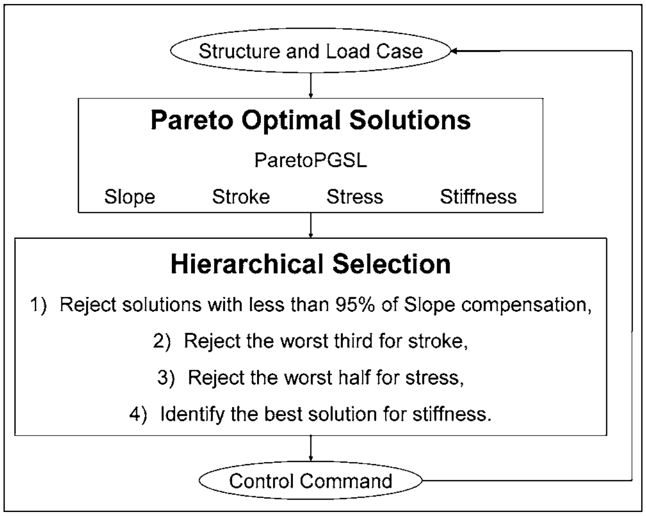

Fig. 4. Multiobjective methodology: Pareto optimal solutions and hierarchical selection

with respect to all objectives but at least one. ParetoPGSL stops after 1,500 generated solutions since preliminary studies showed that solution quality does not improve further.

The selection strategy that is adopted hierarchically reduces the solution space until identification of a control command. It is developed in four steps and reflects the importance of the objectives. Control commands for which slope compensation is less than 95% are first rejected. In practical situations, slope compensation would be acceptable if its value was above this threshold. To keep objectivity with respect to the three remaining objectives, the remaining solutions are divided into thirds according to solution quality. The worst third of the solutions with respect to the stroke objective is rejected. The worst half of the remaining solutions with respect to the stress objective is then rejected. Finally, the best solution with respect to the stiffness objective is identified among solutions that are left. This becomes the control command that is applied to the structure. Therefore, each of the three objectives in the last three steps leads to rejection of the same number of solutions.

Control solutions describe the structural configuration when slopes are compensated. Sequences of application of control commands that transform the altered slope state to the compensated slope state involve verifying that no failure would happen during intermediate steps. The control command is divided into 1 mm steps. Strut contractions are placed at the beginning of the sequence and strut elongations at the end. In this way, energy is generally first taken out of the structure before it is added. Calculations are made using the dynamic relaxation method. The position of the structure is evaluated for each 0.1 mm of actuator travel. The sequence is then applied to the laboratory structure for experimental validation.

Results

This methodology is tested for 24 load cases involving up to two vertical downward point loads from 391 to1,209 N in magnitude (Table 1). A view of the structure from above is showed in Fig. 3. Examine Load Case 5: 859 N point load at node 32. Pareto optimal solutions are generated using the ParetoPGSL algorithm (Fig. 5). Solutions are presented in four dimensions with respect to the four objectives. The slope objective is shown on the vertical axis. Stroke and stress objectives are represented with the horizontal axis. The gray bar evaluates the stiffness objective. Values close to zero are considered best for all objectives.

The first step of the hierarchical selection strategy consists of rejecting all solutions for which slope compensation is less than 95% (Fig. 6). The second step of the selection strategy involves dividing the remaining solution set into three parts according to stroke objective. The worst third is rejected (Fig. 7). The third step of the selection strategy results in dividing the remaining solution set into two parts according to stress objective quality. The worst half is rejected (Fig. 8).

Table 1. Downward Load Cases Applied to the Structure

Load case	Node	Magnitude (N)
1	26	−625
2	26	−900
3	26	−1,209
4	32	−625
5	32	−859
6	32	−1,092
7	37	−391
8	37	−550
9	37	−700
10	48	−391
11	48	−550
12	48	−700
13	6	−1,092
14	37 and 45	−391
15	37 and 45	−624
16	37 and 45	−742
17	39 and 48	−157
18	39 and 48	−215
19	39 and 48	−274
20	41 and 50	−391
21	41 and 50	−624
22	45 and 48	−391
23	45 and 48	−624
24	45 and 48	−742

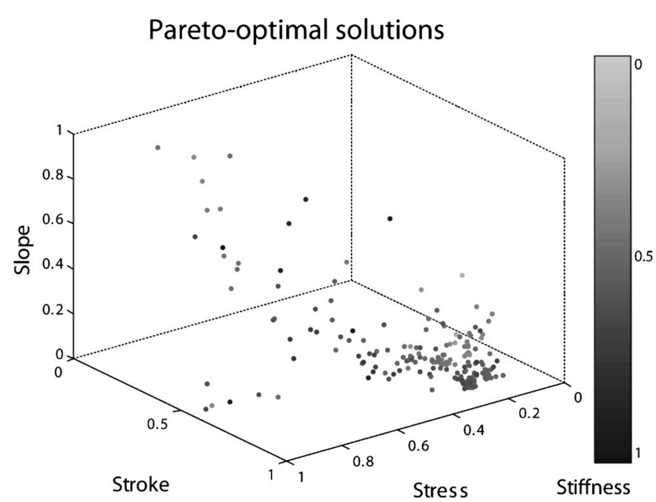

Fig. 5. Pareto optimal solutions with respect to slope, stroke, stress, and stiffness objectives

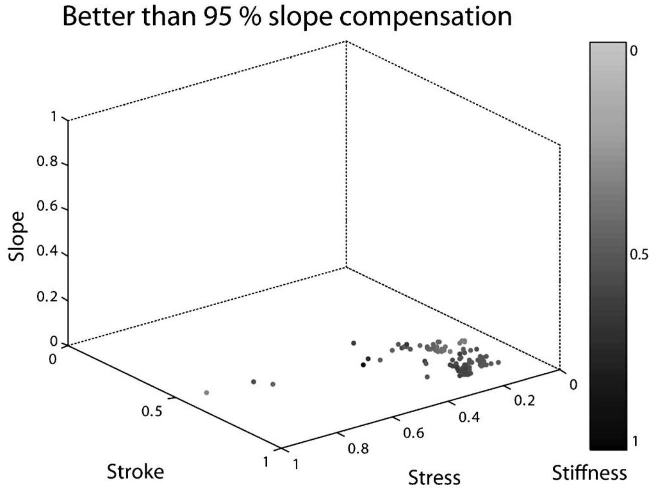

Fig. 6. Solutions for which slope compensation is better than 95%

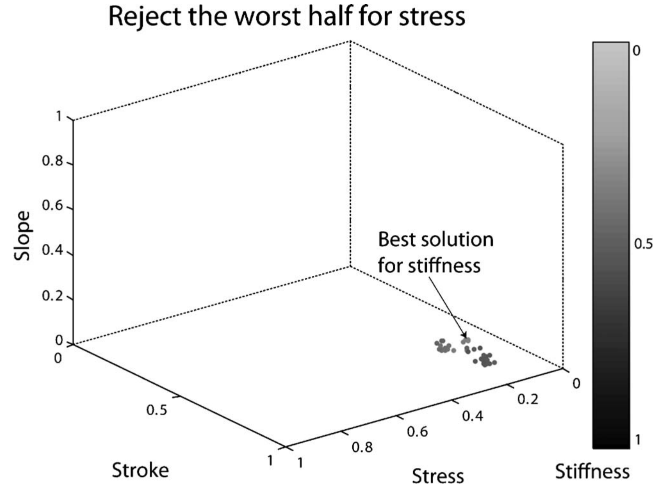

Fig. 8. Solutions for which the worst half of the previous set with respect to stress has been rejected

The last step of the selection strategy consists of identifying the control command as the best solution with respect to stiffness objective (Fig. 8). This solution is the control command that is used to control the structure.

The application sequence of this control command is then calculated to verify that no failure would happen and to observe slope evolution. The control command is applied to the loaded laboratory structure for experimental validation (Fig. 9). Slope deviation evolution is plotted against steps of 1 mm of actuator travel. As said previously, for the purpose of this study, slope unit is millimeter/100 m. Slope deviation is the difference between initial slope and current slope. It is equal to zero when initial slope is recovered. Slope compensation is defined to be

$$SC = \frac{CS - AS}{IS - AS}$$

where CS=corrected slope when the control command has been applied; AS=altered slope; and IS=initial slope. Numerical simulation gives an altered slope deviation of −147 mm/100 m and a corrected slope deviation of 1 mm/100 m (99% compensated). Experimental testing gives an altered slope deviation of −138 mm/100 m and a corrected slope deviation of −4 mm/100 m (97% compensated). The average actuator travel is 1.5 mm. The most tensioned cable at the compensated slope state is cable 15 with 7.8 kN (92% of limit tensile force) whereas the most compressed strut is strut 145 with 17.8 kN (89% of limit compression force). Stress values are only numerical because the structure is not equipped with force sensors that would provide experimental data. Simulation and laboratory test results for slope are generally in good agreement.

Control command robustness improvement is shown in Figs. 10–13 for the 24 load cases listed in Table 1. Comparison of slope compensation between single objective (slope) and multiobjective search for one and two point loads is presented in Fig. 10. Slope compensation quality does not decrease significantly with multiobjective optimization when stroke, stress, and stiffness are also taken into account. Fig. 11 shows the average stroke for commands identified using a single objective and multiobjective methods. In 17 cases out of 24, average stroke is less when the control command is identified with multiobjective search. As multiobjective methods are intended to satisfy multiple objectives, solutions are trade off solutions. Nevertheless, multiobjective solutions are more robust than single objective solutions. Fig. 12 shows the comparison of the limit load ratio of the most stressed

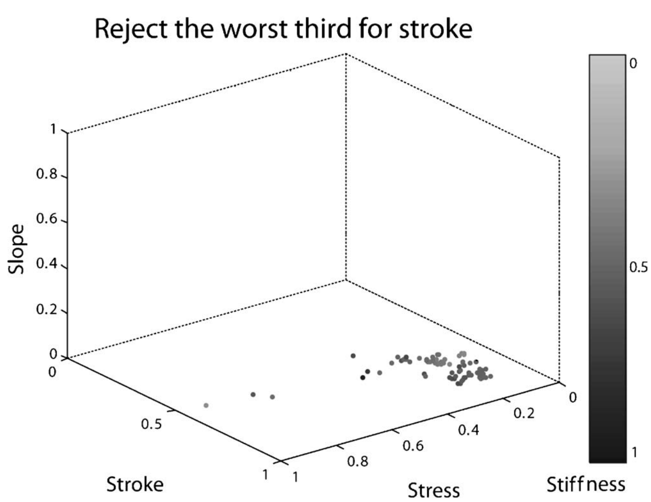

Fig. 7. Solutions for which the worst third of the previous set with respect to stroke has been rejected

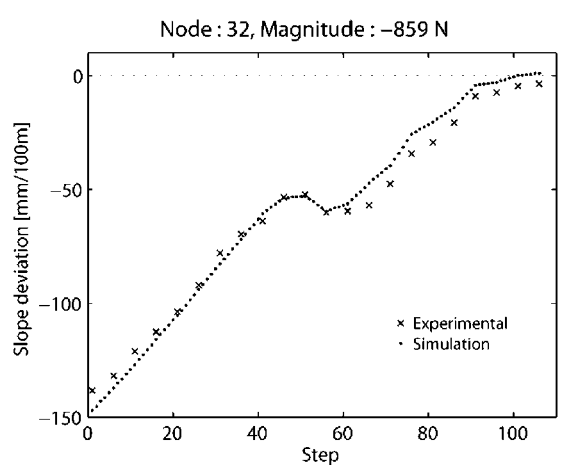

Fig. 9. Experimental and numerical slope compensation sequence

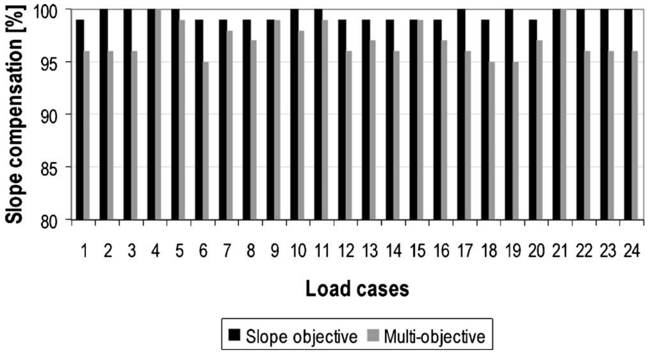

Fig. 10. Slope compensation for one (Load Cases 1–13) and two (Load Cases 14–24) point load

element when slope is compensated, for control command identified using single objective (slope) and multiobjective search. In the 24 cases, the limit load ratio is less when slope is compensated with multiobjective control command. Fig. 13 shows stiffness comparison when slope is compensated with control commands identified using single objective (slope) and multiobjective search. As the stiffness objective is the last objective to be employed it is more difficult to improve stiffness using multiobjective search. Conflicts between objectives are also illustrated in Figs. 10–13. In 5 cases out of 24, control command quality with respect to all three robustness objectives is improved when the control command is identified with multiobjective search. In 18 cases, control command quality is improved for two robustness objectives. Load Case 3 exhibits quality improvement only for the stress objective.

More experimental validation is presented in Fig. 14. Slope compensation correlation between numeric simulation and experimental testing is plotted in this diagram. Very good agreement between experimental testing and numeric simulation can be seen when the point load is placed at nodes 26, 32, 48, 41, 50, or 45, with a correlation between 80 and 100%. Correlation is between 60 and 80% for the other load cases. Deviation between numeric simulation and experimental testing increases when altered slope increases. This is probably due to friction in the connections and to the non-linear effect of the control command application.

These results are obtained from altered slope compensation due to a single loading event. We now introduce the concept of multiobjective serviceability control when the structure is subjected to a scenario of sequentially applied loads. This scenario

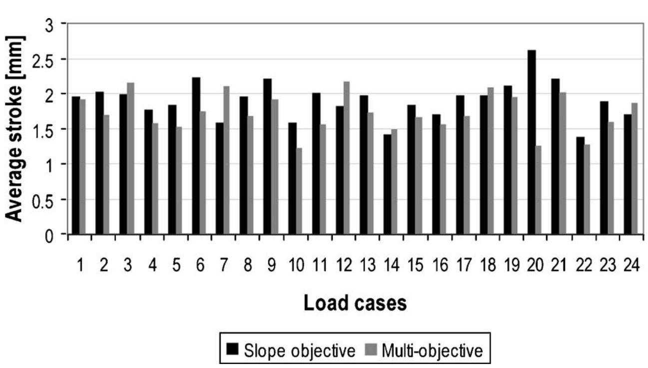

Fig. 11. Average stroke comparison for single objective or multiobjective search, for one (Load Cases 1–13) and two (Load Cases 14–24) point load

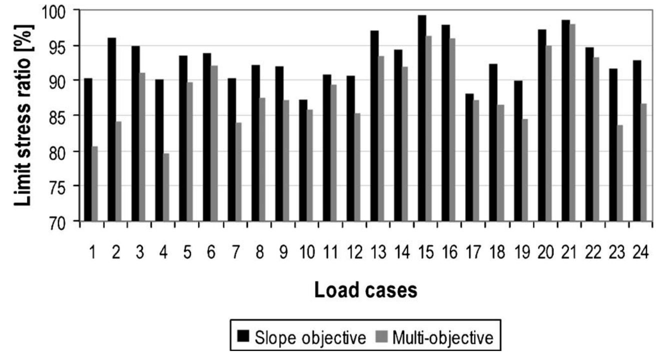

Fig. 12. Limit stress ratio for single objective and multiobjective search, for one (Load Cases 1–13) and two (Load Cases 14–24) point load

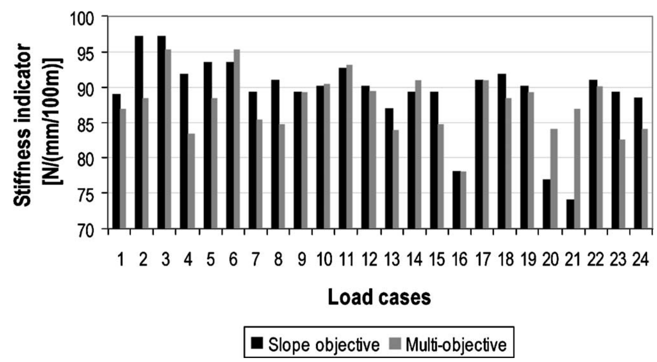

Fig. 13. Stiffness when slope is compensated, for single objective and multiobjective search, for one (Load Cases 1–13) and two (Load Cases 14–24) point load

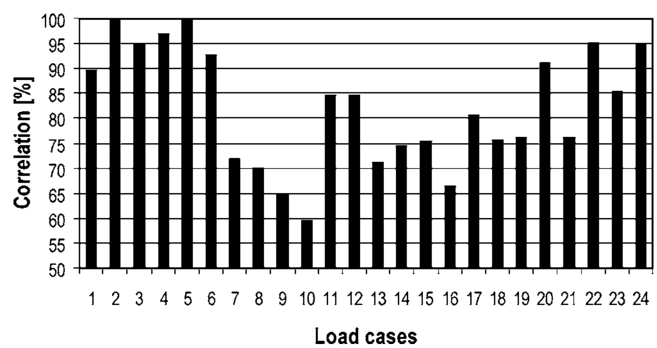

Fig. 14. Slope compensation correlation between numerical simulation and experimental testing, for one (Load Cases 1–13) and two (Load Cases 14–24) point load

simulates multiple control events over service life. To illustrate this situation, consider the multiple load applications presented in Table 2. Structural control for this scenario is presented in Fig. 15. Slope evolution is plotted versus steps of 1 mm of actuator travel. Load events are numbered from 1 to 6. Zero slope deviation means that initial slope is recovered. Structural behavior when control commands are identified using multiobjective search and single objective search are evaluated. Control commands are more rapidly effective when they are identified with multiobjective search. Single objective control commands exhibit

Table 2. Successive Load Event Scenario

Load event	Node	Magnitude (N)
1	32	−391
2	50	−391
3	37	−391
4	48	−391
5	26	−391
6	6	−150

a more pronounced zig-zag profile that requires more steps to correct the slope. Multiobjective commands are useful to maintain robustness of both the structure and the control system whereas in single objective sequence no such maintenance can be assured. At the sixth control command, the multiobjective method makes it possible to compensate the slope whereas a single objective method leads to buckling of a strut.

Conclusions

Control commands are defined according to the load case and four objectives: top surface slope compensation, stroke, stresses, and stiffness. The following conclusions come out of this research:

- Control commands are, in most cases, more robust when determined by multiobjective control as compared with single objective (slope) control;
- In situations where satisfying a dominant objective results in many solutions, a Pareto approach together with hierarchical elimination of solutions is attractive, especially when tasks require single solutions such as during structural control;
- Evaluation of multiple objectives provides a more global understanding of tensegrity structure behavior than any single objective; and
- Multiple load application events are controlled more efficiently using multiobjective control.

These results lead toward more autonomous and self-adaptive structures that evolve in changing environments.

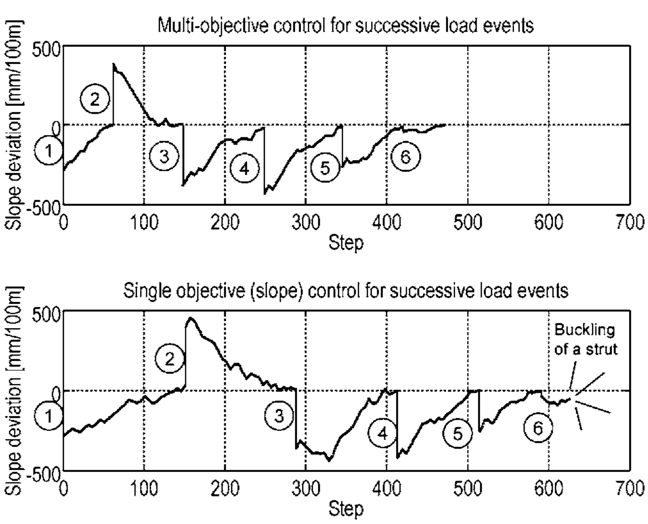

Fig. 15. Successive load events numbered from 1 to 6: Multiobjective and slope-objective control commands behavior

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Notation

The following symbols are used in this paper:

$\boldsymbol{f}$ = vector of objective functions;
$\boldsymbol{g}$ = vector of inequality constraints;
$\boldsymbol{h}$ = vector of equality constraints;
K = structure global stiffness;
N = normal force;
Q = point load;
$\boldsymbol{q}$ = load case set;
S = top surface slope; and
$\boldsymbol{x}$ = decision variables set.

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