CONTROL ENHANCEMENTS OF A BIOMIMETIC STRUCTURE

Ian F.C. Smith
Ecole Polytechnique Fédérale de Lausanne (EPFL), Switzerland
Ian.Smith@epfl.ch

SUMMARY: *Implementation of active control has much potential to contribute to the creation and construction of innovative structures and other building systems such as those needed for climate control. This paper summarizes recent research at EPFL that is evaluating biomimetic civil structures through active geometry control. Intelligent control methodologies that implement stochastic search with case-based reasoning, self-diagnosis, multi-objective shape control, self-repair and reinforcement learning are proposed and validated experimentally on a five-module active tensegrity structure. It is concluded that i) previous control cases improve control performance; ii) self-diagnosis extends active structural control of tensegrity structures to situations where there may be partially defined loading events and damage; iii) multi-objective search is attractive for computing robust commands that control geometry of an active tensegrity structure and iv) the active control system can be used to apply control commands that increase stiffness and decrease stresses within an active tensegrity structure that is damaged. The integration of intelligent control methodologies such as those described in this paper to an active tensegrity structure creates a biomimetic example that could be applied to a range of other building systems.*

REFERENCE: *Smith I (2009) Control enhancements of a biomimetic structure, Journal of Information Technology in Construction (ITcon), Vol. 14, Special Issue Next Generation Construction IT: Technology Foresight, Future Studies, Roadmapping, and Scenario Planning, pg. 229-237, http://www.itcon.org/2009/17*

1. INTRODUCTION

Biomimetic structures are structures that demonstrate increased functionality through mimicking qualities that are normally present only in biological organisms. Examples of such qualities are self-repair and adaptation mechanisms that improve with time. In spite of many qualitative concept papers, little scientific progress has been made on biomimetic structures. Other types of biomimetic building systems are not further ahead. Currently, factors such as advances in computing, wireless technology as well as new sensor and actuator technologies are creating favourable conditions for implementing active control systems in the built environment. Such control systems could provide many innovative solutions, particularly for applications such as temporary and reusable structures as well as providing an example of the possibilities of biomimetic control for other building systems.

While bio-inspired systems have already been studied for decades in domains such as mathematics, informatics, electronics and robotics (Von Neumann, 1966, Denning, 1976, Floreano and Mondada, 1998, Teuscher et al, 2003) few examples of adaptive civil-engineering structures have been found in the literature. Pawlowski and Holnicki-Szulc (2004) introduced a structure that adapts to extreme loads. It detected impacts through a set of sensors and optimally distributed forces in the structure using structural fuses. Sobek et al. (2006) defined adaptive structures as load carrying systems which are able to react to variable external influences. Noak et al. (2006) demonstrated experimentally that integrating actuators in a trussed beam system allows for a significant increase in span and an increased load bearing capacity. However, these are studies where the control command

and the structural response are directly linked and not coupled with other control loops. They are carried out mainly on small models and through numerical simulation. Moreover, no experimental demonstration of self diagnosis and self repair of a full-scale civil engineering structure could be found in the literature. In building physics, some work has studied adaptive control for aspects such as shading, for example, (Guillemin and Morel, 2002).

Since tensegrities can be equipped with active control systems, they have the potential to adapt to their environments. Tensegrities are spatial, reticulated and lightweight structures that are composed of struts and tendons. Stability is provided by the self-stress state between tensioned and compressed elements (Motro, 1984). A recent definition has been proposed by Motro (2003): A tensegrity system is a system in a stable self-equilibrated state comprising a discontinuous set of compressed components within a continuum of tensioned components.

In complex structures, geometric control is necessarily indirect and coupled. Fest et al. (2004) demonstrated experimentally the feasibility of tensegrity active shape control. The most challenging part of the study was the computation of control commands (sequence of contractions and elongations of active struts) that modify the self-stress state in order to recover the top surface slope of the structure when subjected to a load. Since the behaviour of the structure that was used for experimental testing is geometrically nonlinear and highly coupled, there is no closed-form solution for active strut adjustments given a required top surface slope (Fest et al, 2003). This fact precludes the use of analytical treatment such as suggested for example in (Williamson et al, 2003). A single objective stochastic search algorithm (Raphael and Smith, 2003) was selected as the best method to accommodate the exponentially complex generate-test process that is needed to compute control commands (Domer et al, 2003). (Domer and Smith, 2005) studied the capacity of this structure and its control system to learn with the experience of previous calculations in order to decrease the average time necessary to compute a control command.

No other example of full-scale experimental testing of coupled control of a civil engineering structure has been found in the literature. This paper summarizes an example of experimental testing and numerical simulations of an adaptive civil engineering structure using a set of intelligent control methodologies: self diagnosis and self repair (Adam and Smith, 2007a), multi-objective geometric control (Adam and Smith, 2007b) and reinforcement learning (Adam and Smith, 2008). These methodologies are integrated into a full-scale active tensegrity structure to support coupled control in partially defined environments. Finally, the applicability of these results to other building systems is discussed.

2. TEST STRUCTURE

In order for a test environment to demonstrate biomimetic qualities, a system that has many closely coupled elements is required. Controlled parameters should have the potential to influence many parts of the system. Measurement points are placed in areas where the measured quantity can be influenced by several controlled parameters. Objectives are formulated in terms of measured values, the behaviour of the system and the state of the control mechanism. Finally the relationships between the controlled parameters and the measured quantities are non-linear. While these requirements appear to be restrictive, they describe most full-scale systems that stand to benefit from active control.

The structure that is used for experimental testing is the same as in (Fest et al, 2003). It is composed of 5 modules and rests on three supports (Figure 1). It covers a surface area of 15m2, has a height of 1.20m and withstands a distributed dead load of 300N/m2. It is composed of 30 struts and 120 tendons. Struts are fiber reinforced polymer tubes of 60mm diameter and 703mm2 cross section. Tendons are stainless steel cables of 6 mm in diameter. The central node and star topology is a particularity of each module. This topology was proposed to limit buckling lengths, thereby allowing for more slender compression elements than traditional "simplex" tensegrity modules (Fest et al, 2003).
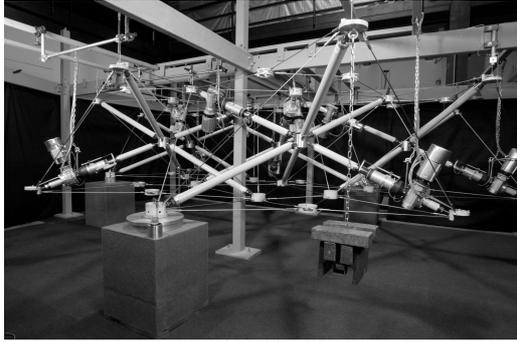
FIG. 1: Five modules, 15 m2 ground projection, 10 active struts, 3 displacement sensors

The structure is equipped with an active control system: ten active struts and three displacement sensors. Pairs of active struts are placed in-line within each module. They allow for strut length adjustment. Displacement sensors measure vertical displacements at three top surface nodes: 37, 43 and 48 (Figure 2). Shape control has involved satisfying a serviceability objective: maintaining the slope of the top surface of the structure when the structure was subjected to loading. Top surface slope S is calculated from the vertical coordinates of the top surface three nodes, z_{37}, z_{43} and z_{48} that are equipped with displacement sensors (Figure 2).
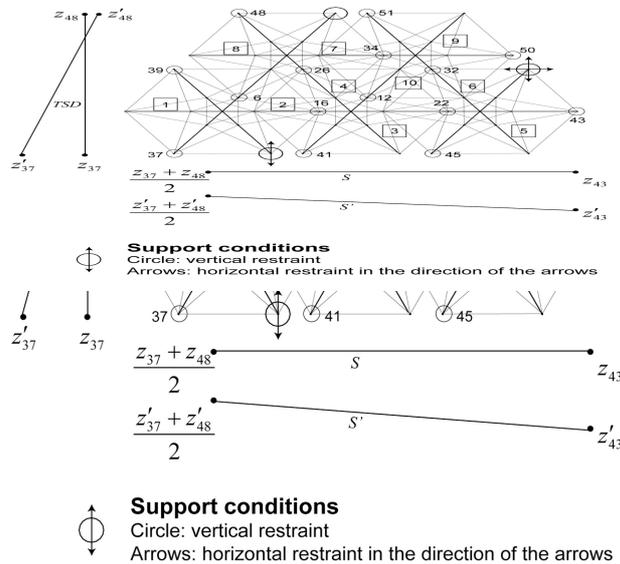
FIG. 2: View from the top of the active tensegrity structure

3. SELF DIAGNOSIS

Loads are single vertical static loads. Load magnitude and location is unknown. Self diagnosis involves magnitude evaluation and location and is carried out using system identification methodology (Smith and Saitta, 2008). Similarly to the inverse problem of control command computation presented in (Fest et al, 2003), there is no closed-form solution for self diagnosis due to geometric non-linearity. In spite of this, system identification in this study requires no additional measurements.

The response of the structure to a load and damage is measured and compared to the response of the structure to candidate solutions for load and damage. Three indicators that reflect changes in structure response are used: top surface slope deviation, transversal slope deviation and influence vectors. Since maintaining the top surface slope is the main shape control objective, it is also used as the main indicator. Top surface slope variations are induced by active control perturbations. Active control perturbations are defined as a 1 mm elongation of active struts.

The transversal slope deviation indicator is used to evaluate the transversal behavior of the structure. This indicator is measured on the structure and then compared with the behavior of possible solutions that are calculated through numerical simulation. Top surface slope variations induced by each of the ten active struts are put together in order to create influence vectors, the third indicator. These vectors express the top surface slope variation per mm of active strut elongation. Since tensegrities are self-stressed and flexible structures, they exhibit geometric nonlinear behavior. Damage and applied loads induce changes in response to active control perturbations. Effects are observed through modifications of the influence vectors measured on the structure and this is compared with calculations using numerical simulation.

The load identification involves magnitude evaluation and load location. The methodology uses these three indicators. In this study, loading is assumed to be single static vertical point loads. They are applied one at a time on one of the 15 top surface nodes. The following steps lead to load identification:

Step 1: Top surface slope deviation is the first indicator. Once the structure is loaded, magnitude evaluation involves numerically determining, for each of the 15 top surface nodes, which load magnitude can induce a top surface slope deviation that is close to the one measured on the structure. This evaluation is performed iteratively for each node j of the top surface. Load magnitudes are gradually increased by 50N increments until the top-surface-slop-deviation calculation exceeds the measured value. Value pairs of load magnitudes and locations create a set of candidate solutions. Negative loads (upward) are not considered.

Step 2: Transversal slope deviation is the second indicator. Trends must be the same. Candidate solutions that do not demonstrate changes in the same slope direction are rejected. Experiments show that 2.9mm/100m is an upper bound for measurement error of transversal slope deviation. In situations where the absolute value of transversal slope deviation is less than 2.9mm/100m, no candidate solution is rejected. This difference between measurements and numerical simulation is related to measurement and modeling errors.

Step 3: The influence vector is the third indicator. It includes slope variations per mm of active strut elongations. The influence vector is determined from measurements. Slope variations resulting from active control perturbations are measured. For remaining candidate solutions, the influence vector is evaluated through numerical simulation of active control perturbations. The candidates that have differences between measurements and calculations below a certain threshold are taken to be candidate solutions.

Step 4: For each of these solutions, load magnitudes are modified to approach more closely measured top surface slope deviation with 10N increments. Improved candidates create the load identification solution set. In this set, the distance between candidate solution responses and measurements is less or equal to the maximum error between measurements and numerical simulation. Load identification solutions are used as input to compute a control command for the shape control task.

While several candidate solutions may be generated, the control commands that follow always satisfy the control objective within acceptable limits. More details are provided in (Adam and Smith, 2007a).

A broken cable can also be detected through observing structural behaviour during small actuator movements. When subjected to dead load only and for the initial self-stress level, only one tenth of the cables and all struts are critical elements (leading to progressive collapse). Critical cables are mostly located at the edge of the structure where loads can not pass through other elements without causing a failure.

For non critical elements, trends in behaviour indicators are measured and compared with stored simulated values for damaged structures. A set of candidate positions for cable rupture is thus iteratively filtered to obtain the correct position. In a similar way to the task of load identification, the top surface slope deviation and the influence vector are used as indicators for damage location (Figure 6). Damage is simulated by removing one cable from the structure. For damage location, a candidate is defined as the structure with one cable removed. The following steps are carried out:

Step 1: Top surface slope deviationis the first indicator. Local damage induces top surface slope deviation that is measured on the damaged structure. Since 91 elements are non critical, 91 candidate solutions are considered. Top surface slope deviation is numerically simulated for each candidate solution. A maximal error of 96mm/100m has been observed for simulated values of top surface slope deviation compared with values of top surface slope deviation that are measured on the structure for a particular damage situation . This error is related to model inaccuracies. Candidate solutions are retained in situations where differences between measurements and calculations are less than this error.

Step 2: The influence vector is the second indicator. Active control perturbations are numerically simulated for candidate solutions to calculate slope variations. In situations where instabilities are observed due to active control perturbations, the damage location process stops. However, this phenomenon has not been observed during experimental testing. Active control perturbations are applied to the damaged structure. Candidate solutions have differences between measurements and numerical simulation that are less or equal to an threshold that is determined through an evaluation of measurement and modeling error.

4. MULTI-OBJECTIVE CONTROL

Since there is no closed-form solution for control command computation for shape control of this structure and since there are ten control commands, the generate-and-test stochastic search process usually generates many tens of possible solutions. Multi-objective search is then used to select good control commands according to four criteria. In practical contexts, active structures need to continue their usefulness as loads change. While shape control in this study involves maintaining the top surface slope of the structure when subjected to a load, this objective should not be met in isolation. Robustness of both the structure and the active control system is also important. In this study, robustness of the structure is related to serviceability and safety. Robustness of the active control system is expressed in terms of active strut stroke. In situations of active control, robustness is required to accommodate multiple load and control events over service lives.

Additional objectives are used to avoid limits of safety and serviceability. The following objectives are relevant:

- Slope: maintain top surface slope
- Stress: minimize stress ratio of the most stressed element
- Stroke: maintain active strut jacks as close as possible to their midpoint
- Stiffness: maximize structural stiffness

The two first objectives are related to robustness of the structure. The third objective insures robustness of the active control system. The fourth objective is intended to ensure adequate stiffness of the structure for the next loading event. These four objectives are not complementary. Adam and Smith (2007a) contains details on how these criteria are evaluated.

The methodology for multi-objective geometric control is based on Pareto filtering and hierarchical selection. The selection strategy 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.

A testing program involving 24 load cases consisting of up to two vertical downward point loads from 391 N to 1209 N in magnitude. Several tests involved active control over successive loading events. While single objective control resulted in cable rupture after only a few loading events, multi-objective control resulted in much greater ability to maintain structural integrity.

The following conclusions come out of this research:

- Control commands are, in most cases, more robust when determined by multi-objective 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.

- Multiple load application events are controlled more efficiently using multi-objective control.

5. SELF REPAIR

Once the position of the broken cable is established in the structure, self repair control commands are calculated using multi-objective control applied to the following two criteria: maximize structural stiffness and minimize stresses in highly stressed elements. While it was often possible to satisfy the original control goal (slope), reducing the negative effects of damage proved to be more challenging.

The methodology for computing self-repairing control commands is based on Pareto filtering in order to avoid the use of weight factors. Sets of Pareto optimal solutions are built according to the stiffness and the stress objectives. Moreover, since this multi-objective search supports control command computing, one single solution has to be automatically selected. While the slope objective is now of tertiary importance, among sets of Pareto optimal solutions for stress and stiffness, solutions that exhibit the highest slope compensation are taken to be the solution for the self-repairing control command.

Through experimental testing Adam and Smith (2007a) demonstrated that it is possible to control using objectives such as stiffness and stress by modifying the self-stress state of an active tensegrity structure that has had a cable removed. Therefore, self repair has the potential to be supported by active control systems for active structures. When the damage location solution is exact, self repair is attractive for active structures in situations of partially defined damage. When damage location is not exact, self repair might lead to stress increase. Additional information, for example stress measurements, would be useful to improve damage location.

While it was observed for the first time that stiffness can be increased and stresses reduced through active control commands on a damaged structure, repair was only partial and clearly only possible when alternative load paths existed. This aspect of the research is thus a qualified success to date; more work is needed to identify more precisely the conditions where self repair is effective.

6. LEARNING

Reinforcement learning is used to improve control performance. Although the learning algorithm employs case-based reasoning, which is often classified as a weak form of supervised learning, it has evolved into reinforcement learning since it learns from errors in order to support incremental improvements of control commands. The learning algorithm is divided into memorization, retrieval, adaptation and replacement processes.

After successful self diagnosis and multi-objective shape control, a case is memorized. A case is composed of the following components: case attributes, control command, slope compensation, see (Adam and Smith, 2008) for more details. Case attributes are the response of the structure in terms of top surface slope deviation and other response indicators. The control command is composed of ten active strut elongations and contractions. The last component is the slope compensation that is measured on the structure when the control command was applied. This measurement data allows the structure to learn from the relative success of previous commands as well as through reuse of previous control command calculations.

Cases are retrieved according to similarity measures that are determined through comparisons with case attributes and measurements on the structure. Once a case is retrieved, its control command is adapted for shape control of the structure subjected to current load. The adaptation function is based on an assumption of locally linearity (Adam and Smith, 2008). In situations where the control command that is adapted from a retrieved case leads to slope compensation improvement, the current case replaces the retrieved case. In this way, the structure reacts better and more quickly to applied control commands as it gains experience. Case base maintenance is also assured in this way.

The learning methodology has been verified over 80 loading and control events. The following observations and remarks are relevant:
- The methodologies for retrieval and adaptation generally allow for control quality and control rapidity improvement over retrieved cases.
- Since current cases replace retrieved cases when control quality improves, better cases are gradually stored and naturally classified in the case base. However, case attributes of replaced cases are also replaced. This leads to a loss of information.
- The reinforcement learning algorithm can be seen as an iterative method over retrieved cases that successfully accommodates nonlinear behavior.

- Geometrically nonlinear behavior of tensegrity structures can momentarily slow down the learning process.
- Control performance may decrease momentarily. Since control is performed over random loading events, cases may momentarily not be retrieved.
- The derivative of the evolution of the number of cases in the case base decreases as retrieved cases are replaces by new cases over 80 loading and control events.
- It is expected that after about 150 random loading events, cases are retrieved for each control event.

It is concluded that the learning algorithm allows for two types of learning: decreased time for control command computation and increased control command quality as cases are retrieved and adapted. Although case-based reasoning is normally classified as supervised learning, the proposed learning methodology proposed in this work contributes to reinforcement learning. Interaction between learning algorithms and sensor devices is attractive for improving control tasks.

7. APPLICABILITY TO OTHER BUILDING SYSTEMS

Although the control strategies described in this paper have been conceived and tested within the field of structural engineering, there are opportunities to adapt these results to other building systems. For the best exploitation of the strategies described in this paper, the following is a list of *system characteristics* that are appropriate:

- There is no closed-form solution for control commands given desirable behaviour as input. Since the tensegrity structure behaves in a geometrically non-linear manner, simple strategies such as superposition of weighted components of an inverted influence matrix are not successful. Similarly, there is usually no closed-form solution, for example, for determining climate-control commands in a building to achieve low energy use for a given outside environment and required use of space.

- There are relatively fast ways to estimate behaviour given control commands. In structural engineering this is performed by traditional structural analysis methods. Similarly, recent building physics research has resulted in efficient simulation packages using modern computer hardware.

- Sensors are available to measure relevant behaviour characteristics. The relationships between sensor measurements and control commands are indirect and coupled. A single control command will influence measurement results at many sensor locations. This is the case for most building systems.

- Actuators are present that modify system behaviour.

- System elements can fail and this requires cycles of self diagnosis and adaptation to revised system characteristics in order to satisfy control criteria. Building systems need to be robust and biomimetics can help achieve robustness in efficient ways.

- Multiple control criteria are important for operation. Current strategies assume that one criterion is dominant and that many control command sets are capable of optimizing performance. Other criteria then filter command sets to identify the command set that provides robustness in terms of objectives such as subsequent performance.

The beneficiaries of biomimetic control systems include designers, owners and occupants. Designers are given greater freedom to explore innovative solutions that may not satisfy traditional conservative operating restrictions. Owners receive cost-effective building systems that minimize intervention after element failure and reduce costs of failures. Users benefit from increased building functionality and more generally, higher quality of life. It is expected that rudimentary systems will be available in the next three years. Full implementation of computational control using advanced informatics to include optimization methods, model-based system identification, data mining and machine learning is likely to require five to fifteen years depending on future research support.

8. CONCLUSIONS

The most important conclusions of the work to date are:

- Geometric non-linearity and closely coupled behavior mean that there is no closed-form solution for control commands given criteria such as required geometry. Stochastic search techniques are useful for avoiding the difficulties related to exponentially complex brut-force search.

- Previous control cases improve control performance. Over time, the structural system learns.

- Self diagnosis extends active structural control of tensegrity structures to situations where there may be partially defined loading events and damage.

- Multi-objective search is attractive for computing commands that control shape of an active tensegrity structure while maintaining robustness of both the structure and the active control system. These commands are particularly useful for controlling structures over scenarios of multiple loading events. This advantage is expected to be fully transferable to other building systems.

- Self repair of a damaged active tensegrity structure is possible. The active control system can be used to apply control commands that increase stiffness and decrease stresses within an active tensegrity structure that is damaged.

- Reinforcement learning is attractive for improving the control of an active tensegrity structure using previous loading events. Improvements involve lower command computation times and better control quality. Such interactions between learning algorithms and active control systems are attractive for control tasks and potentially many building systems could benefit.

The integration of intelligent control methodologies such as self diagnosis, multi-objective shape control, self repair and reinforcement learning to an active tensegrity structure creates an example of an adaptive civil structure that can be applied to a range of other practical situations in the future. More specifically, other control systems, such as those for indoor climate, energy use, water systems and occupant movements could be improved through biomimetic enhancements such as the ones described in this paper. All of these applications are potential areas for future work.

Acknowledgements

References

Adam, B. and Smith, I.F.C. (2007a). "Self -Diagnosis and Self -Repair of an Active Tensegrity Structure", Journal of Structural Engineering, Vol 133, 2007, pp 1752-1761.

Adam, B. and Smith, I.F.C. (2007b). "Tensegrity Active Control: a Multi-Objective Approach", Journal of Computing in Civil Engineering, Vol 21, No 1, 2007, pp 3-10.

Adam B. and Smith I.F.C. (2008). "Reinforcement Learning for Structural Control", Journal of Computing in Civil Engineering, Vol 22, No 1, 2008, pp 133-139.

Denning P.J. (1976). "Fault Tolerant Operating Systems", ACM Computing survey, 8(4), 359-389.

Domer B., Raphael B., Shea K. and Smith I.F.C. (2003). "A study of two stochastic search methods for structural control", Journal of Computing in Civil Engineering, 17(3), 132-141.

Domer B., and Smith I.F.C. (2005). "An Active Structure that learns", Journal of Computing in Civil Engineering, 19(1), 16-24.

Fest E., Shea K. and Smith I.F.C. (2004). "Active Tensegrity Structure", Journal of Structural Engineering, 130(10), 1454-1465.

Fest E., Shea K., Domer B. and Smith I.F.C. (2003). "Adjustable Tensegrity Structure", Journal of Structural Engineering, 129(4), 515-526.

Floreano D. and Mondada F. (1998). "Evolutionary neurocontrollers for autonomous mobile robots", Neural Networks, (11), 1461-1478.

Guillemin A. and Morel N. (2002). "Application of genetic algorithms to adapt an energy efficient shading device controller to the user wishes" EPIC 2002, AIVC Conference Proceeding, Lyon.

Motro R. (1984). "Forms and forces in tensegrity systems", In:Nooshil, H. (Ed.), Proceedings of Third International Conference on Space Structures. Elsevier, Amsterdam, 180-185.

Motro R. (2003). "Tensegrity: Structural systems for the future", Hermes, ed., Penton Science, U.K., 280.

Noak T., Ruth J., and Müller U. (2006). "Adaptive Hybrid Structures", Proceedings of the International Conference on Adaptable Building Structures, Adaptables2006, Eindhoven, The Netherlands, 03-05 July 2006.

Pawlowski P., and Holnicki-Szulc J. (2004). "Adaptive Structures under Extreme Loads – Impact detection, Self-adaptation, Self-repairing", Proceedings of the Third European Conference on Structural Control, Vienna, Austria.

Raphael B., and Smith I.F.C. (2003). "A direct stochastic algorithm for global search", J of Applied Mathematics and Computation, 146(2-3), 729-758.

Smith I.F.C. and Saitta, S. (2008) "Improving Knowledge of Structural System Behavior through Multiple Models" Journal of Structural Engineering, Vol 134, No 4, pp 553-561.

Sobeck W., Teuffel P., Weilandt A. and Lemaitre C. (2006). "Adaptive and Lightweight", Proceedings of the International Conference on Adaptable Building Structures, Adaptables2006, Eindhoven, The Netherlands, 03-05 July 2006.

Teuscher C., Mange D., Stauffer A., and Tempesti G. (2003). "Bio-inspired computing tissues: towards machine that evolve, grow, and learn", BioSystems, 68, 235-244.

Von Neumann J. (1966). "The theory of Self-Reproducing Automata" University of Illinois Press, Urbana.

Williamson D., Skelton R.E. and Han J. (2003). "Equilibrium conditions of a tensegrity structure", International Journal of Solids and Structures, 40, 6347-6367.