ON COMBINED PLANT AND CONTROL OPTIMIZATION

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ABSTRACT

Due to their coupling, solving the plant and control optimization problems sequentially does not guarantee system optimality. Numeric, experimental, and set theoretic demonstrations of this coupling are reviewed. The coupling is quantified using comparisons of first order necessary conditions for plant, control and combined optimality. Combined optimization strategies are categorized and compared. Two nested strategies are shown to guarantee system optimality and used to find optimal combinations of passive and active vibration control in elevators and car suspensions. These optimal combinations outperform their passive, active and sequentially optimized counterparts in the time and frequency domains.

KEYWORDS: Plant/Control Optimization – Plant/Control Optimality Conditions – Nested Optimization – Optimal Passive/Active Mix

1. INTRODUCTION

In designing a controlled or “smart” artifact, traditionally one optimizes the underlying controlled subsystem (*plant*) first, then the control. Despite simplifying system design problems by partitioning them along interdisciplinary boundaries into smaller and more tractable plant and control design subproblems, such sequential optimization fails to guarantee system optimality by failing to account for the *coupling* between these subproblems. This paper reviews the numerical, experimental and mathematical demonstrations of this coupling (Section 2). Quantitative measures of the coupling are derived from original comparisons of first-order necessary conditions for plant, control and combined optimality (Section 3). Combined plant/control optimization strategies are classified (Section 4), and two nested strategies are shown to guarantee system optimality (Section 5). Applying these nested strategies to combined passive/active vibration control in car suspensions and elevators produces systems that outperform their passive, active and sequentially optimized passive/active counterparts in the time and frequency domains (Section 6). Finally, new directions for combined plant/control optimization research are outlined (Section 7).

2. DEMONSTRATIONS OF COUPLING

Research in several application areas has demonstrated the coupling between the plant and control optimization problems from two perspectives. First, in systems comprising actively controlled passive plants, the coupling is manifested by competition between sequentially optimized plants and controls. In the field of flexible space structure design, for example, Smith *et al.* [1] observed that sequential structure/control optimization produced unnecessarily stiff passive structures whose active vibration control hence required more energy and was consequently less robust. Similarly, Ulsoy *et al.* [2] observed that in combined active/passive car suspensions, active control gains acted to oppose the underlying passive structures and replace them with “sky-hook” elements, thereby expending more energy and exhibiting less robustness than the truly optimal suspension systems.

The coupling between the plant and control optimization problems is highlighted further by the suboptimality of sequentially optimized plant/control designs. In the field of reconfigurable manufacturing, for instance, O'Neal *et al.* [3] showed that designing a flexible boring bar and its cutting tool position controller simultaneously, as opposed to sequentially, enabled more accurate machining. Similarly, Reyer and Papalambros [4] showed that optimizing a DC motor's design and control simultaneously, as opposed to sequentially, gave better system performance. In the field of aeroservoelasticity, Sahasrabudhe *et al.* [5] showed that neglecting the interactions between a helicopter's rotor elasticity and flight control system could lead to underperforming and even unstable helicopter designs, and Karpel [6] and Livne [7] introduced integrated aeroservoelasticity models capturing this and other aspects of the coupling between the aeroelastic and servocontrol optimization problems.

In addition to these numerical demonstrations of the coupling, the literature also reports experimental ones. Asada and coworkers experimentally optimized a flexible robot manipulator's structural design to make it easier to control, and subsequently found the new manipulator to outperform the traditional, sequentially optimized one [8]. Similarly, Haftka *et al.* [9] and Maghami *et al.* [10] modeled two actively controlled flexible structures, redesigned them together with their controls using integrated optimization techniques, and showed that they required significantly less actuation for the same performance provided by their sequentially optimized counterparts. Finally, the present authors [11] demonstrated the coupling experimentally using a simple setup comprising a DC electric motor receiving a constant input voltage v_{in} and driving a sheave that pulls a mass M upward (Fig. 1). Treating the payload M as the plant design variable, the voltage v_{in} as the control design variable (the controller in this case being a simple bang-bang one) and the weighted objective T+1/M (where T is the time needed by this model elevator to lift the payload from rest through a predefined height) as the system optimization goal, the authors optimized this setup experimentally by determining the objective function values for different payloads and bang-bang voltages. The results (shown in Figure 2) reveal that optimizing the setup sequentially by assuming an initial control design, say v_{in}=2.5V, optimizing the plant for that control, then optimizing the control for the resulting plant, gave a design (indicated as P1 in Fig. 2) significantly inferior to the system optimum (indicated as P2 in Fig. 2).

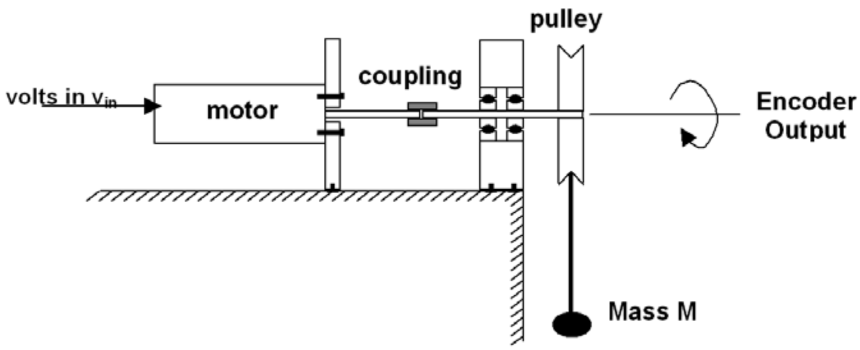

Figure 1: Experimental Setup

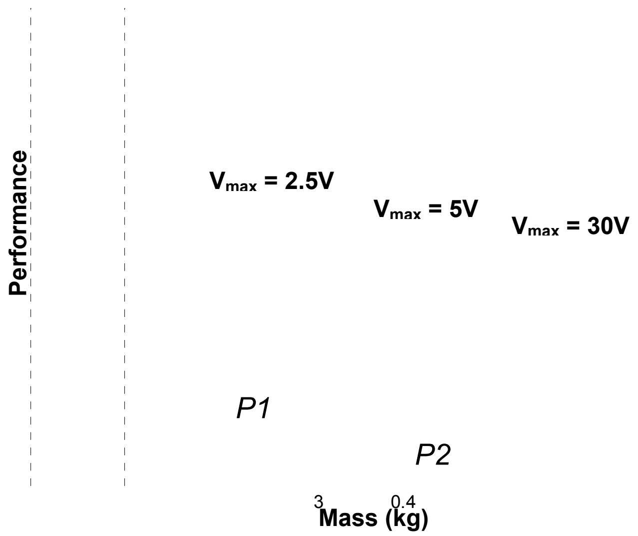

Figure 2: Experimental Results

The present authors [12] also demonstrated the coupling between the plant and control optimization problems mathematically for the problem

$$\min_{(\mathbf{x}_p,\mathbf{x}_c)\in\mathbf{X}} \{w_p f_p(\mathbf{x}_p) + w_c f_c(\mathbf{x}_p,\mathbf{x}_c)\}\,, \tag{1}$$

where $\mathbf{x}_p$ and $\mathbf{x}_c$ denote the plant and control variables, respectively, $\mathbf{X}$ is the set of feasible systems, f_p and f_c are the respective plant and control objectives, and w_p and w_c are the respective plant and control optimization weights in an assumed linear scalarization of the plant/control Pareto optimization problem. This formulation assumes unidirectional coupling, where the plant design affects the control objective, but not vice versa. Though not universal, such a formulation covers most plant/control optimization problems in the literature. Defining the sets $\mathbf{X}_p$, $\mathbf{X}_p(\mathbf{x}_c)$, and $\mathbf{X}_c(\mathbf{x}_p)$ of feasible plants, feasible plants for a given control design, and feasible control designs for a given plant, respectively, as

$$\mathbf{X}_p = \{\mathbf{x}_p : \exists\mathbf{x}_c : (\mathbf{x}_p,\mathbf{x}_c)\in\mathbf{X}\}\,,\ \mathbf{X}_p(\mathbf{x}_c) = \{\mathbf{x}_p : (\mathbf{x}_p,\mathbf{x}_c)\in\mathbf{X}\}\,,$$
$$\mathbf{X}_c(\mathbf{x}_p) = \{\mathbf{x}_c : (\mathbf{x}_p,\mathbf{x}_c)\in\mathbf{X}\}\,, \tag{2}$$

one can define Direct Sequential Optimization (DSO) as that strategy where the plant is optimized for an initial control design guess, $\mathbf{x}_c^i$ (usually open-loop control), then the control is optimized for the resulting plant, i.e.,

$$\mathbf{x}_p^{DSO} = \arg\min_{\mathbf{x}_p\in\mathbf{X}_p(\mathbf{x}_c^i)} \{w_p f_p(\mathbf{x}_p) + w_c f_c(\mathbf{x}_p,\mathbf{x}_c^i)\}\,,\ \mathbf{x}_c^{DSO} = \arg\min_{\mathbf{x}_c\in\mathbf{X}_c(\mathbf{x}_p^{DSO})} \{f_c(\mathbf{x}_p^{DSO},\mathbf{x}_c)\}\,. \tag{3}$$

Furthermore, one can define Projected Sequential Optimization (PSO) as that strategy where the plant objective is optimized over the set of feasible plants, then the control objective is optimized for the resulting plant, i.e.,

$$\mathbf{x}_p^{PSO} = \arg\min_{\mathbf{x}_p\in\mathbf{X}_p} f_p(\mathbf{x}_p)\,,\ \mathbf{x}_c^{PSO} = \arg\min_{\mathbf{x}_c\in\mathbf{X}_c(\mathbf{x}_p^{PSO})} \{f_c(\mathbf{x}_p^{PSO},\mathbf{x}_c)\}\,. \tag{4}$$

Given these definitions, the present authors showed using set theory that DSO and PSO both generally fail to guarantee system optimality, except in certain special cases. Notably, if one applies PSO to a problem where the plant objective is infinitely more important than the control objective (i.e., $w_p/w_c \rightarrow \infty$) or fortuitously starts DSO with an initial controller design guess, $\mathbf{x}_c^i$, for which an optimal system exists, then system optimality is guaranteed.

Sequential optimization hence fails to guarantee system optimality by optimizing the plant for open-loop - rather than optimal - control and by implicitly assuming the plant objective to be infinitely more important than the control objective. Both assumptions are often unjustified and ignore the coupling between the plant and control optimization problems. This coupling becomes a more crucial aspect of controlled system design when performance requirements are tightened and plant uncertainties increase, as explained by Youcef-Toumi [13] and proven by Brusher *et al.* [14] and Cakmakci [15] for the somewhat similar integrated modeling and control design problem. Increased plant uncertainties and tighter performance requirements both characterize today's challenging engineering design problems, and hence there is an increasing need for precise understanding and quantification of the coupling between the plant and control optimization problems. Such quantification is presented in the following section.

3. QUANTIFICATION OF COUPLING

Assuming plant and control linearity and time-invariance and partitioning the control design problem into estimation and regulation subproblems, this section poses combined plant/estimator, plant/regulator and plant/estimator/regulator optimization problems. First order necessary conditions for optimality of these problems (assuming continuity, differentiability and regularity at optima) are reported from Fathy *et al.* [16] and used in conjunction with the well-known KKT, Potryagin and Wiener-Hopf optimality conditions to quantify the bilateral and trilateral couplings between the optimal plant, estimation and regulation design problems. Certainty equivalence precludes the existence of bilateral coupling between the optimal estimation and regulation problems. To quantify the remaining bilateral and trilateral couplings, consider the plant/regulator optimization problem,

$$\min_{\mathbf{x}_p,\mathbf{u}(t),\mathbf{z}(t),t_o,T} \left\{ w_p f_p(\mathbf{x}_p) + w_c \left\{ \Phi(\mathbf{z}(T),T) + \int_{t_o}^{T} L(\mathbf{z}(t),\mathbf{u}(t),t)dt \right\} \right\} \text{ subject to: } \mathbf{h}_p(\mathbf{x}_p) = \mathbf{0},$$

$$\mathbf{g}_p(\mathbf{x}_p) \le \mathbf{0},\ \dot{\mathbf{z}}(t) = \mathbf{f}(\mathbf{z}(t),\mathbf{u}(t),t,\mathbf{x}_p),\ \eta(\mathbf{u}(t),t,\mathbf{x}_p) \le \mathbf{0},\ \Psi(\mathbf{x}(T),T) = \mathbf{0},\ \mathbf{z}(t_o) = \mathbf{z}_o, \quad (5)$$

the plant/estimator optimization problem,

$$\min_{\mathbf{x}_p,\mathbf{L}(t,\tau)} \left\{ w_p f_p(\mathbf{x}_p) + w_o \left[\mathbf{z}(\mathbf{x}_p,T) - \int_0^T \mathbf{L}(\tau,T)\mathbf{y}(\mathbf{x}_p,\tau)d\tau \right]^T \left[\mathbf{z}(\mathbf{x}_p,T) - \int_0^T \mathbf{L}(\tau,T)\mathbf{y}(\mathbf{x}_p,\tau)d\tau \right] \right\}$$

$$\text{subject to: } \mathbf{h}_p(\mathbf{x}_p) = \mathbf{0},\ \mathbf{g}_p(\mathbf{x}_p) \le \mathbf{0}, \quad (6)$$

and the plant/estimator/regulator optimization problem,

$$\min_{\mathbf{x}_p,\mathbf{z}(t),\mathbf{u}(t),\mathbf{y}(t),\mathbf{K},\mathbf{L}(\mathbf{t},\tau)} w_p f_p(\mathbf{x}_p) + w_{oc} \mathrm{E}\int_0^\infty (\mathbf{z}^T(t)\mathbf{Q}\mathbf{z}(t) + \mathbf{u}^T(t)\mathbf{R}\mathbf{u}(t))dt$$

$$\text{subject to: } \mathbf{h}_p(\mathbf{x}_p) = \mathbf{0},\quad \mathbf{g}_p(\mathbf{x}_p) \le \mathbf{0},\ \dot{\mathbf{z}}(t) = \mathbf{A}(\mathbf{x}_p)\mathbf{z}(t) + \mathbf{B}(\mathbf{x}_p)\mathbf{u}(t) + \mathbf{G}(\mathbf{x}_p)\mathbf{w}(t),$$

$$\mathbf{y}(t) = \mathbf{C}(\mathbf{x}_p)\mathbf{z}(t) + \mathbf{v}(t),\ \mathrm{E}(\mathbf{v}(t)\mathbf{v}^T(\tau)) = \mathbf{V}\delta(t,\tau),\ \mathrm{E}(\mathbf{w}(t)\mathbf{w}^T(\tau)) = \mathbf{W}\delta(t,\tau),$$

$$\mathbf{u}(t) = -\mathbf{K}\mathbf{z}_e(t),\ \mathbf{z}_e(t) = \int_0^t \mathbf{L}(\tau,t)\mathbf{y}(\tau)d\tau\,. \quad (7)$$

Here, the control design variables are the state, input, output and state estimate trajectories **z**(t), **u**(t), **y**(t) and $\mathbf{z}_e$(t), respectively, plus the state feedback gain matrix **K** and a non-clairvoyant mapping **L**(t,τ) between the measurement and observation Hilbert spaces enumerating the estimator design. Stationarity and ergodicity are assumed where appropriate. Zero-mean, uncorrelated, white and Gaussian disturbance and noise signals with covariances **W** and **V** afflict the system, and the estimation and regulation objectives are, respectively, the resulting mean square state estimation error at time T and the sum of the expectations of the norms of the state and control vectors, weighted by positive semidefinite and positive definite matrices **Q** and **R**, respectively. The system objective is a weighted sum of the plant, estimation and regulation objectives, where w_p, w_c, w_o and w_{or} denote scalarization weights. PSO simplifies each of these three problems by optimizing the plant, i.e.,

$$\min_{\mathbf{x}_p} f_p(\mathbf{x}_p) \quad \text{subject to: } \mathbf{h}_p(\mathbf{x}_p) = \mathbf{0},\ \mathbf{g}_p(\mathbf{x}_p) \le \mathbf{0}, \tag{8}$$

then optimizing either the regulator, i.e.,

$$\min_{\mathbf{u}(t),\mathbf{z}(t),t_o,T} \Phi(\mathbf{z}(T),T) + \int_{t_o}^{T} L(\mathbf{z}(t),\mathbf{u}(t),t)dt \tag{9}$$

subject to: $\dot{\mathbf{z}}(t) = \mathbf{f}(\mathbf{z}(t),\mathbf{u}(t),t,\mathbf{x}_p)$, $\eta(\mathbf{u}(t),t,\mathbf{x}_p) \le \mathbf{0}$, $\Psi(\mathbf{x}(T),T) = \mathbf{0}$, $\mathbf{z}(t_o) = \mathbf{z}_o$,

or estimator, i.e.,

$$\min_{\mathbf{L}(t,\tau)} \left[\mathbf{z}(\mathbf{x}_p,T) - \int_0^T \mathbf{L}(\tau,T)\mathbf{y}(\mathbf{x}_p,\tau)d\tau \right]^T \left[\mathbf{z}(\mathbf{x}_p,T) - \int_0^T \mathbf{L}(\tau,T)\mathbf{y}(\mathbf{x}_p,\tau)d\tau \right], \tag{10}$$

or both, i.e.,

$$\min_{\mathbf{z}(t),\mathbf{u}(t),\mathbf{y}(t),\mathbf{K},\mathbf{L}(\mathbf{t},\tau)} \mathrm{E}\int_0^\infty (\mathbf{z}^T(t)\mathbf{Q}\mathbf{z}(t) + \mathbf{u}^T(t)\mathbf{R}\mathbf{u}(t))dt \quad \text{subject to: } \mathbf{z}_e(t) = \int_0^t \mathbf{L}(\tau,t)\mathbf{y}(\tau)d\tau$$

$$\dot{\mathbf{z}}(t) = \mathbf{A}(\mathbf{x}_p)\mathbf{z}(t) + \mathbf{B}(\mathbf{x}_p)\mathbf{u}(t) + \mathbf{G}(\mathbf{x}_p)\mathbf{w}(t),\ \mathbf{y}(t) = \mathbf{C}(\mathbf{x}_p)\mathbf{z}(t) + \mathbf{v}(t), \tag{11}$$
$$\mathrm{E}(\mathbf{v}(t)\mathbf{v}^T(\tau)) = \mathbf{V}\delta(t,\tau),\ \mathrm{E}(\mathbf{w}(t)\mathbf{w}^T(\tau)) = \mathbf{W}\delta(t,\tau),\ \mathbf{u}(t) = -\mathbf{K}\mathbf{z}_e(t).$$

Such a sequential approach gives plants obeying the Karush-Kuhn-Tucker (KKT) conditions,

$$\mathbf{h}_p(\mathbf{x}_p) = \mathbf{0},\ \mathbf{g}_p(\mathbf{x}_p) \le \mathbf{0},\ \exists(\alpha \ne \mathbf{0}, \beta \ge \mathbf{0}):\ \beta^T\mathbf{g}_p = \mathbf{0},\ \frac{d}{d\mathbf{x}_p}\left(f_p + \mathbf{h}_p^T\alpha + \mathbf{g}_p^T\beta\right) = \mathbf{0} \tag{12}$$

estimators satisfying the Wiener-Hopf equation,

$$\mathrm{cov}[\mathbf{z}(T),\mathbf{y}(\sigma)] + \int_0^T \mathbf{L}(T,\tau)\,\mathrm{cov}[\mathbf{y}(\tau),\mathbf{y}(\sigma)]d\tau = \mathbf{0} \qquad \forall \sigma \in [0,T] \tag{13}$$

and regulators satisfying the differential form of the Pontryagin minimum principle,

$$\dot{\mathbf{z}}(t) = \mathbf{f}(\mathbf{z}(t),\mathbf{u}(t),t,\mathbf{x}_p),\ \eta(\mathbf{u}(t),t,\mathbf{x}_p) \le \mathbf{0},\ \Psi(\mathbf{x}(T),T) = \mathbf{0},\ \mathbf{z}(t_o) = \mathbf{z}_o,$$
$$\exists(\nu \ne \mathbf{0}, \lambda(t) \ne \mathbf{0}, \mu(t) \le \mathbf{0}, H = L + \lambda^T\mathbf{f}):\ \partial H/\partial\mathbf{u} = \left(\partial\eta/\partial\mathbf{u}\right)^T \mu,\ \partial H/\partial\mathbf{z} = d\lambda/dt, \tag{14}$$
$$\mu^T\eta = 0,\ \left[\partial\Phi/\partial t + (\partial\Psi/\partial t)^T\nu + L - \lambda^T\mathbf{f}\right]_T dT + \left[\partial\Phi/\partial\mathbf{z} + (\partial\Psi/\partial\mathbf{z})^T\nu + \lambda\right]_T d\mathbf{z}(T) = 0.$$

Necessary conditions for plant/regulator, plant/estimator and plant/estimator/regulator optimality (for Eqs. (5-7)) contain the Wiener-Hopf and Pontryagin conditions, but differ from the KKT conditions by the coupling terms in Eqs. (15-17), respectively,

$$-\frac{w_c}{w_p}\int_{t_o}^{T}((\partial \mathbf{f}/\partial \mathbf{x}_p)^T \lambda + (\partial \eta/\partial \mathbf{x}_p)^T \mu)dt\,, \tag{15}$$

$$\frac{w_o}{w_p}\frac{dE_{ms}^*}{d\mathbf{x}_p}\,, \tag{16}$$

$$\frac{w_{or}}{w_p}\frac{df_{oc}^*}{d\mathbf{x}_p}\,, \tag{17}$$

where E_{ms}^* and f_{or}^* are the optimal mean square state estimation error at time T and the optimal LQG performance index for a given plant, respectively. Besides quantifying the bilateral and trilateral couplings between the plant, estimator and regulator optimization problems, these coupling terms provide tests for decoupling. A system's plant and control (i.e., regulation or estimation or both) optimization problems decouple (in the sense that solving them sequentially guarantees system optimality) only if their coupling term at the sequential optimum belongs to a subspace spanned by locally active plant constraints. If such decoupling does not occur, a simultaneous (or equivalent) optimization strategy is needed for attaining system optimality. Plant/control optimization strategies are reviewed below.

4. PLANT/CONTROL OPTIMIZATION STRATEGIES

The literature presents many plant/control optimization strategies, grouped by Reyer and Papalambros [4] into sequential, simultaneous, iterative and nested ones (Fig. 3). Compared to sequential strategies, simultaneous ones afford guaranteed system optimality, but require large disparate teams to solve complex multidisciplinary optimization problems collaboratively. Iterative and nested strategies maintain the simpler interdisciplinary partitioning used in sequential ones, while attempting to guarantee system optimality. Iterative strategies optimize a plant for fixed control, then optimize the control, fixing the plant, and so on until convergence. While often reducing system optimization problems to convergent sequences of convex plant and control optimization problems [1], iterative strategies generally fail to guarantee system optimality [4]. Nested strategies, on the other hand, do guarantee system optimality, as shown in Section 5.

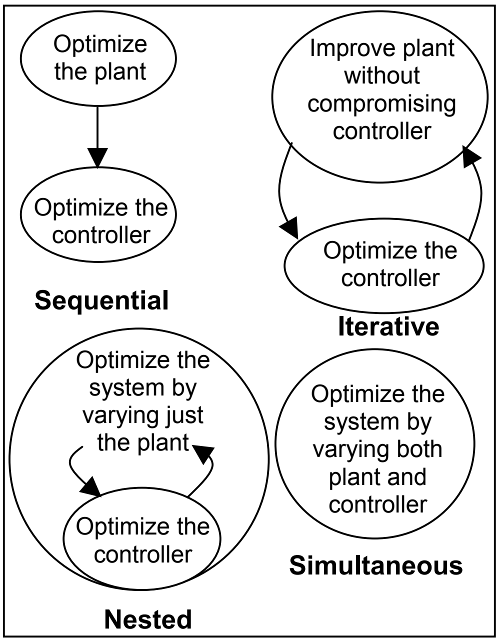

Fig. 3: Strategies for plant/controller optimization

5. NESTED PLANT/CONTROL OPTIMIZATION

A nested plant/control optimization strategy comprises two nested loop: an outer loop where the system objective is optimized over the set of feasible plants, and an inner one that generates optimal controls for plants chosen by the outer loop. Defined mathematically as:

Outer loop: $\mathbf{x}_p^* = \arg\min_{\mathbf{x}_p \in \mathbf{X}_p} w_p f_p(\mathbf{x}_p) + w_c f_c(\mathbf{x}_p, \mathbf{x}_c^*(\mathbf{x}_p))$, (18)

Inner loop: $\mathbf{x}_c^*(\mathbf{x}_p) = \arg\min_{\mathbf{x}_c \in \mathbf{X}_c(\mathbf{x}_p)} f_c(\mathbf{x}_p, \mathbf{x}_c)$, (19)

nested optimization has been shown by the present authors to guarantee system optimality [12]. The nested strategy in Eqs. (18-19) assumes *a priori* availability of the set $\mathbf{X}_p$ of feasible plants: a valid assumption for linear and time-invariant systems where the only combined plant/control constraint is closed-loop stability. For other situations, the present authors have developed nested strategies that do not require *a priori* availability of $\mathbf{X}_p$. Nested optimization is applied in Section 6 to two combined passive/active vibration control problems.

6. OPTIMAL PASSIVE/ACTIVE VIBRATION CONTROL EXAMPLES

Optimizing a car suspension's passive and active subsystems (Fig. 4) for different weights on the active control energy objective revealed to the present authors [17] that the optimal car vibration control system is neither passive nor active nor a sequentially optimized mix of both, but rather a system-optimal blend of both obtained using nested optimization (Fig. 5).

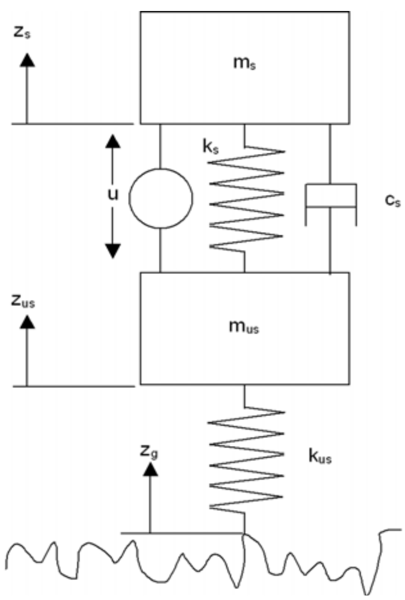

Fig. 4: Suspension Model

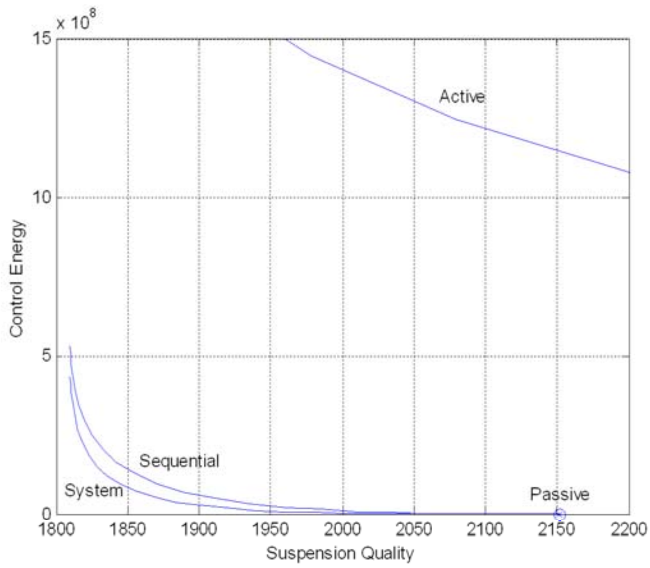

Fig. 5: Suspension Optimization Results

Optimizing an elevator's plant and gain-scheduled LQG control system using nested optimization also gave a superior elevator system compared to sequential optimization [18].

7. DISCUSSION AND CONCLUSIONS

The plant and control optimization problems are coupled in the sense that solving them sequentially does not guarantee system optimality. This paper reviewed demonstrations of such coupling in the literature and reviewed the authors' contributions to its study and mitigation. Specifically, the paper analyzed the coupling using set theory, quantified it by comparing deterministic and stochastic conditions for combined plant/control optimality to the KKT, Pontryagin and Wiener-Hopf conditions, presented nested optimization strategies guaranteed to mitigate the coupling and find system optima, and applied those strategies to combined passive/active vibration control. Future work will pursue the link between a system's robustness and the coupling between the optimization of its plant and control.

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