Front. Mech. Eng. 2019, 14(1): 102–112
https://doi.org/10.1007/s11465-019-0527-0

FEATURE ARTICLE

A. Galip ULSOY

Smart product design for automotive systems

Abstract Automobiles evolved from primarily mechanical to electro-mechanical, or mechatronic, vehicles. For example, carburetors have been replaced by fuel injection and air-fuel ratio control, leading to order of magnitude improvements in fuel economy and emissions. Mechatronic systems are pervasive in modern automobiles and represent a synergistic integration of mechanics, electronics and computer science. They are smart systems, whose design is more challenging than the separate design of their mechanical, electronic and computer/control components. In this review paper, two recent methods for the design of mechatronic components are summarized and their applications to problems in automotive control are highlighted. First, the combined design, or co-design, of a smart artifact and its controller is considered. It is shown that the combined design of an artifact and its controller can lead to improved performance compared to sequential design. The coupling between the artifact and controller design problems is quantified, and methods for co-design are presented. The control proxy function method, which provides ease of design as in the sequential approach and approximates the performance of the co-design approach, is highlighted with application to the design of a passive/active automotive suspension. Second, the design for component swapping modularity (CSM) of a distributed controller for a smart product is discussed. CSM is realized by employing distributed controllers residing in networked smart components, with bidirectional communication over the network. Approaches to CSM design are presented, as well as applications of the method to a variable-cam-timing engine, and to enable battery swapping in a plug-in hybrid electric vehicle.

Keywords mechatronics, automotive control, co-design, component swapping modularity, active suspensions, variable camshaft timing engine, plug-in hybrid electric vehicle

Received August 1, 2018; accepted September 3, 2018

A. Galip ULSOY (✉)
Department of Mechanical Engineering, University of Michigan, Ann Arbor, MI 48109-2125, USA
E-mail: ulsoy@umich.edu

1 Introduction

One of the things that most clearly distinguishes humans from other species in the animal kingdom is that humans make and use tools. The famous fluid mechanician Theodore von Karman once stated [1]: "A scientist studies what is, whereas an engineer creates what never was." Figure 1 captures the same notion of the engineer as a creator of physical artifacts (i.e., the tools used to shape the world), in contrast to the scientist who studies the physical world [2]. Of course, there are no neat and sharp divisions of the disciplines as schematically indicated in Fig. 1, and any engineering task can draw significantly from the sciences, arts and humanities. Consequently, we see an increasing emphasis on interdisciplinarity in engineering education.

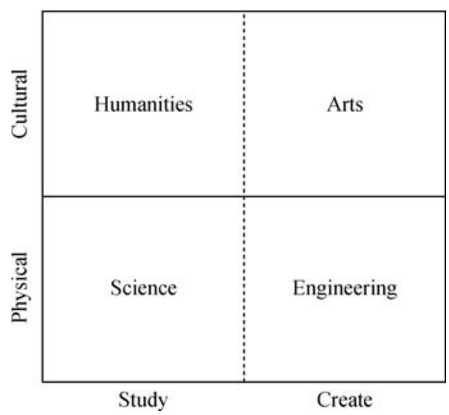


Fig. 1 A classification of the disciplines humanities, arts, sciences and engineering. Engineering is the discipline associated with creating physical artifacts

The world we experience in our daily lives is very much an engineered, and not at all a natural, world. Buildings, roads, cars, trains, sewer lines, clean water supplies, electric power, computers, smart phones, internet, satellites, and many other engineered systems profoundly effect our lives every day. Furthermore, the pace of engineering innovation is accelerating, and many of these engineered systems we take for granted in our daily lives are products of only the past century and many more engineering innovations (e.g., fusion-based energy, low-cost solar energy, virtual reality, secure cyberspace, autonomous cars) are expected in the coming century [3,4]. Engineers, and their innovations, literally and rapidly change the world we live in.

For example, the editors of *MIT Technology Review*, in February 2003, identified "10 Emerging Technologies That Will Change the World" [5]. One of those 10 technologies is *Mechatronics*, and the editors stated: "To improve everything from fuel economy to performance, automotive researchers are turning to mechatronics, the integration of familiar mechanical systems with new electronic components and intelligent-software control. Take brakes. In the next 5 to 10 years, electromechanical actuators will replace hydraulic cylinders; wires will replace brake fluid lines; and software will mediate between the driver's foot and the action that slows the car." Thus, the century old automobile, the preferred mode for personal mobility throughout the world, is rapidly becoming a complex electro-mechanical system, with dozens of networked microprocessors in every vehicle [6]. Various new electro-mechanical technologies are being added to automobiles to improve operational safety, reduce congestion and energy consumption, and minimize environmental impact. Current vehicles often include many new features, which were not widely available even just a few decades ago. Examples include electric or hybrid powertrains, electronic engine and transmission controls, cruise and headway control, anti-lock brakes, differential braking, vehicle stability systems, and active/semi-active suspensions. Many of these functions can be, and have been, achieved using purely mechanical devices. The major advantages in using electro-mechanical (or mechatronic) devices, as opposed to their purely mechanical counterparts include: (1) The ability to embed knowledge about the system behavior into the design of the system itself, (2) the flexibility inherent in these systems to trade-off among different goals, and (3) the potential to coordinate the functioning of subsystems. Knowledge about system behavior, in terms of vehicle, engine or even driver dynamic models, or constraints on physical variables, are included in the design of these electro-mechanical systems. Flexibility enables adaptation to the environment, thus providing more reliable performance under a wide variety of conditions. Furthermore, re-programmability implies lower cost through exchangeable parts and reuse. Exchange of information makes it possible to integrate sub-systems and obtain superior performance and functionality, which are not possible with un-coordinated systems. Thus, these are smart systems whose engineering design is more challenging than simply the separate and sequential design of their mechanical, electronic and computer/control components.

In this article, two recent methods for the design of such mechatronic systems, or smart products, are summarized and their applications to problems in automotive control are highlighted. First the combined design, or *co-design*, of a smart artifact and its controller is considered [7–31]. It is shown that the combined design of an artifact and its controller can lead to improved performance compared to sequential design (i.e., design the artifact first, then design its controller). The coupling between the artifact and controller design problems is quantified, and methods for co-design are presented. The *control proxy function* (CPF) method, which provides ease of design as in the sequential approach and approximates the performance of the co-design approach, is highlighted with application to the design of a passive/active automotive suspension. Second, the design for *component swapping modularity* (CSM) of a distributed controller for a smart product is discussed [32–50]. CSM is realized by employing distributed controllers residing in networked smart components, with bidirectional communication over the network. Several approaches to CSM design are presented and discussed. Applications of the method to a variable-cam-timing engine, and to enable battery swapping in a plug-in hybrid electric vehicle, are highlighted.

2 Coupling between artifact and controller design problems

Mechatronic systems, or smart products, arise in the design of many modern engineered systems. For example, actively controlled structures such as lightweight satellites and bridges must minimize both weight and vibrations. Robots and automated machines also need to minimize weight, while achieving high accuracy and repeatability. Micro-electro-mechanical systems (MEMS) must achieve a range of motion with fast response and high accuracy. Consequently, smart products typically require the design of a mechanical artifact (e.g., a lightweight solar panel, a linear axis) as well as the design of a controller for that artifact (e.g., active vibration suppression, axis controller). Traditionally, one first designs the artifact, then given that artifact designs the controller, in a *sequential* design process. Such a sequential design process often works well, and leads to good results. However, numerous studies in the literature have clearly demonstrated that the *combined*, or simultaneous, design of the artifact and its controller can lead to better performance. The quantification of the coupling between the artifact and controller design problems is considered in the next subsection. When the coupling between these two design problems is zero (or weak) one can use the traditional sequential approach and achieve excellent performance. If the coupling is strong, then a co-design approach is needed to achieve system optimality, and various approaches to co-design have been considered and are summarized. One approach, discussed in the second subsection, is to use a

CPF, which can provide the system optimal results (or near system optimal results) of a co-design while maintaining the ease of design (both organizationally and computationally) of the sequential design approach.

2.1 Coupling between artifact and controller design problems

Consider an *artifact design problem*, formulated as a constrained minimization problem:

$$\min f_{\mathrm{a}}(\boldsymbol{d}_{\mathrm{a}}), \tag{1}$$

subject to

$$\begin{cases} \boldsymbol{g}_{\mathrm{a}}(\boldsymbol{d}_{\mathrm{a}}) \leqslant 0 \\ \boldsymbol{h}_{\mathrm{a}}(\boldsymbol{d}_{\mathrm{a}}) = 0 \end{cases}. \tag{2}$$

The artifact objective function, f_{a}, is to be minimized subject to inequality constraints, $\boldsymbol{g}_{\mathrm{a}}$, and equality constraints, $\boldsymbol{h}_{\mathrm{a}}$, with respect to the artifact design variables, $\boldsymbol{d}_{\mathrm{a}}$. Similarly, one can define a *controller design problem* as

$$\min f_{\mathrm{c}}(\boldsymbol{d}_{\mathrm{a}},\boldsymbol{d}_{\mathrm{c}}), \tag{3}$$

subject to

$$\begin{cases} \boldsymbol{g}_{\mathrm{c}}(\boldsymbol{d}_{\mathrm{a}},\boldsymbol{d}_{\mathrm{c}}) \leqslant 0 \\ \boldsymbol{h}_{\mathrm{c}}(\boldsymbol{d}_{\mathrm{a}},\boldsymbol{d}_{\mathrm{c}}) = 0 \end{cases}. \tag{4}$$

The controller objective function, f_{c}, is to be minimized subject to inequality constraints, $\boldsymbol{g}_{\mathrm{c}}$, and equality constraints, $\boldsymbol{h}_{\mathrm{c}}$, with respect to the vector of artifact design variables, $\boldsymbol{d}_{\mathrm{a}}$ and the controller design variables, $\boldsymbol{d}_{\mathrm{c}}$. The optimal design problems in Eqs. (1)–(4) are said to exhibit *unidirectional coupling*, since the control design problem depends on $\boldsymbol{d}_{\mathrm{a}}$ and $\boldsymbol{d}_{\mathrm{c}}$, but the artifact design problem depends only on $\boldsymbol{d}_{\mathrm{a}}$. In this review only unidirectional coupling is considered, since many design problems for smart products can be formulated as such. The more general bidirectional coupling case, where f_{a}, $\boldsymbol{g}_{\mathrm{a}}$, and $\boldsymbol{h}_{\mathrm{a}}$ also depend on $\boldsymbol{d}_{\mathrm{c}}$, is discussed in Refs. [10,15,23,25].

The traditional, *sequential*, approach is to first solve the artifact design problem in Eqs. (1) and (2) to obtain $\boldsymbol{d}_{\mathrm{a}} = \boldsymbol{d}_{\mathrm{a}}^*$, then fix the value of the artifact design variables as $\boldsymbol{d}_{\mathrm{a}} = \boldsymbol{d}_{\mathrm{a}}^*$ in Eqs. (3) and (4) while solving for the controller design variables $\boldsymbol{d}_{\mathrm{c}}$. Alternatively, one can also formulate a combined, or simultaneous, or *co-design*, problem as

$$\min\{w_{\mathrm{a}}f_{\mathrm{a}}(\boldsymbol{d}_{\mathrm{a}}) + w_{\mathrm{c}}f_{\mathrm{c}}(\boldsymbol{d}_{\mathrm{a}},\boldsymbol{d}_{\mathrm{c}})\}, \tag{5}$$

subject to:

$$\begin{cases} \boldsymbol{g}_{\mathrm{a}}(\boldsymbol{d}_{\mathrm{a}}) \leqslant 0 \\ \boldsymbol{h}_{\mathrm{a}}(\boldsymbol{d}_{\mathrm{a}}) = 0 \\ \boldsymbol{g}_{\mathrm{c}}(\boldsymbol{d}_{\mathrm{a}},\boldsymbol{d}_{\mathrm{c}}) \leqslant 0 \\ \boldsymbol{h}_{\mathrm{c}}(\boldsymbol{d}_{\mathrm{a}},\boldsymbol{d}_{\mathrm{c}}) = 0 \end{cases}, \tag{6}$$

where w_{a} and w_{c} ($w_{\mathrm{a}}+ w_{\mathrm{c}}= 1$) are the weights assigned to the artifact and controller design objectives, respectively, and the minimization is carried out with respect to both the artifact, $\boldsymbol{d}_{\mathrm{a}}$, and controller, $\boldsymbol{d}_{\mathrm{c}}$, design variables.

First-order necessary conditions for optimality of optimal design problems such as Eqs. (1) and (2), Eqs. (3) and (4) or Eqs. (5) and (6), with both equality and inequality constraints, are termed the Karush-Kuhn-Tucker (KKT) conditions. If one derives the KKT conditions for the co-design problem in Eqs. (5) and (6) and compares them to the KKT conditions for the sequential design problem (i.e., first solve Eqs. (1) and (2) for $\boldsymbol{d}_{\mathrm{a}}^*$, then solve Eqs. (3) and (4) for $\boldsymbol{d}_{\mathrm{c}}^*$, given $\boldsymbol{d}_{\mathrm{a}}^*$), there is only one term that is different [8,10]:

$$\Gamma_{\mathrm{v}} = \frac{w_{\mathrm{c}}}{w_{\mathrm{a}}}\frac{\partial f_{\mathrm{c}}^*}{\partial \boldsymbol{d}_{\mathrm{a}}} = \frac{w_{\mathrm{c}}}{w_{\mathrm{a}}}\left(\frac{\partial f_{\mathrm{c}}}{\partial \boldsymbol{d}_{\mathrm{a}}} + \frac{\partial f_{\mathrm{c}}}{\partial \boldsymbol{d}_{\mathrm{c}}}\frac{\mathrm{d}\boldsymbol{d}_{\mathrm{c}}}{\mathrm{d}\boldsymbol{d}_{\mathrm{a}}}\right). \tag{7}$$

Consequently, one can refer to Γ_{v} in Eq. (7) as the *coupling vector*, which quantifies the coupling between the plant and controller optimization problems by considering the influence of plant design on the optimal attainable control objective. The Euclidean norm of this vector, evaluated at the optimal solution, can be used to characterize the coupling strength between the artifact and controller design problems. Specifically, when the coupling vector is zero one is said to have *objective decoupling*. When the coupling vector is non-zero, but active constraints prevent the system from achieving a zero value of the coupling vector, one is said to have *constraint decoupling*. When either of these decoupling conditions are satisfied, the artifact design problem in Eqs. (1) and (2) and the controller design problem in Eqs. (3) and (4) become decoupled. Thus, yielding a sequential solution, which is identical to the co-design solution. When the two design problems are not decoupled, the solution to the sequential problem will not be as good as the solution to the co-design problem. A more general measure of coupling, applicable to systems with bi-directional coupling, and with more than two coupled design problems, can be found in Refs. [15,23,25]. In this review paper, our discussion is restricted to the coupling measure given by the vector Γ_{v} in Eq. (7).

While some systems are uncoupled, or weakly coupled, many systems do exhibit strong coupling. In particular, uncertainty in system parameters and stringent performance requirements can both lead to strongly coupled systems. In such cases traditional sequential optimization is not recommended, but how then should such coupled artifact/controller design problems best be solved? Figure 2 schematically illustrates various proposed approaches to solving such coupled design problems. These include iterative methods, which can include nesting and partitioning, to try to retain the simplicity and convenience of the sequential solution approach while providing the system optimal solutions available via

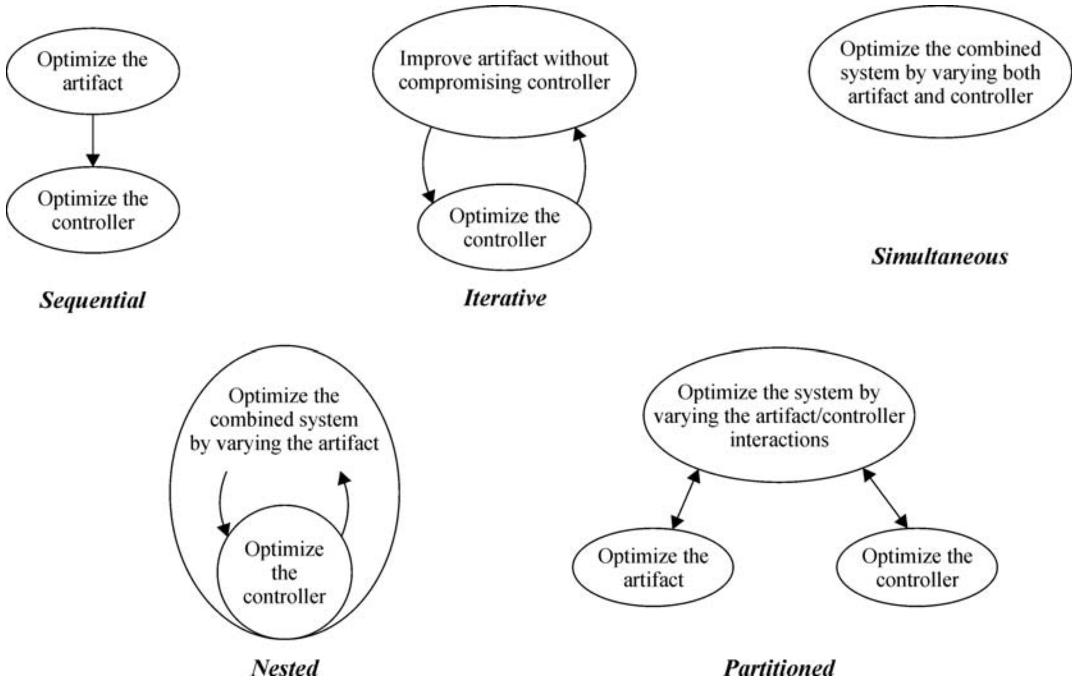


Fig. 2 Solution methods for coupled systems

co-design (*aka* combined design or simultaneous design). The iterative methods, depending on the problem, may or may not converge to the system optimal solution available via co-design. One successful iterative solution method uses the coupling vector in Eq. (7) to "steer" the solution to that which would have been obtained via co-design [28]. A co-design solution is generally not easy to obtain. Computationally it typically leads to non-convex optimization, which can often be a combined static and dynamic optimization. Furthermore, it is organizationally inconvenient as well, since many engineering organizations will have separate engineering groups with expertise in the artifact design and the controller design, respectively. Consequently, it is desirable to have solution methods that can provide the convenience of a sequential approach, while providing the solution of a co-design approach.

2.2 Control proxy function

As noted in the previous subsection, the traditional sequential design, where we first solve Eqs. (1) and (2) then solve Eqs. (3) and (4), provides a very convenient design approach but does not necessarily yield the system optimal solution that one would achieve by solving the co-design problem in Eqs. (5) and (6). Thus, researchers have considered the possibility of modifying the sequential approach to obtain system optimal results while preserving the convenience of the sequential approach. One proposal is to modify the artifact design problem in Eqs. (1) and (2) such that the resulting artifact becomes, in some sense, easier to control in the second step (i.e., Eqs. (3) and (4)). Researchers have proposed, and tried, various methods, and the CPF method is described in the following [22,23,26,29,31].

Consider a modified artifact design problem, formulated as a constrained minimization problem:

$$\min\{f_{\mathrm{a}}(\boldsymbol{d}_{\mathrm{a}}) + \alpha\chi(\boldsymbol{d}_{\mathrm{a}})\}, \tag{8}$$

subject to

$$\begin{cases} \boldsymbol{g}_{\mathrm{a}}(\boldsymbol{d}_{\mathrm{a}}) \leqslant 0 \\ \boldsymbol{h}_{\mathrm{a}}(\boldsymbol{d}_{\mathrm{a}}) = 0 \end{cases}. \tag{9}$$

The new artifact objective function, $f_{\mathrm{a}} + \alpha\chi$, is to be minimized subject to inequality constraints, $\boldsymbol{g}_{\mathrm{a}}$, and equality constraints, $\boldsymbol{h}_{\mathrm{a}}$, with respect to the vector of artifact design variables, $\boldsymbol{d}_{\mathrm{a}}$. The scalar function $\chi(\boldsymbol{d}_{\mathrm{a}})$ is the CPF and α is a weight. If the designer can choose an appropriate CPF and a weight, then the solution to this modified sequential problem could be equal to, or close to, the solution obtained via co-design. Various CPFs (e.g., natural frequencies) have been suggested in the literature, and here a scalar function of the steady-state controllability Gramian is considered:

$$\chi(\boldsymbol{d}_{\mathrm{a}}) = 1/\det(\boldsymbol{W}_{\mathrm{c}}^{\infty}), \tag{10}$$

where for a linear time invariant dynamic system, $\dot{\boldsymbol{x}}(t) = \boldsymbol{A}(\boldsymbol{d}_{\mathrm{a}})\boldsymbol{x}(t) + \boldsymbol{B}(\boldsymbol{d}_{\mathrm{a}})\boldsymbol{u}(t)$, the steady-state controllability Gramian is defined as

$$\boldsymbol{W}_{\mathrm{c}}^{\infty}=\int_{0}^{\infty}\mathrm{e}^{\boldsymbol{A}(\boldsymbol{d}_{\mathrm{a}})t}\boldsymbol{B}(\boldsymbol{d}_{\mathrm{a}})\boldsymbol{B}^{\mathrm{T}}(\boldsymbol{d}_{\mathrm{a}})(\mathrm{e}^{\boldsymbol{A}(\boldsymbol{d}_{\mathrm{a}})t})^{\mathrm{T}}\mathrm{d}t, \tag{11}$$

and can be obtained as the solution to the Lyapunov equation:

$$\boldsymbol{A}(\boldsymbol{d}_{\mathrm{a}})\boldsymbol{W}_{\mathrm{c}}^{\infty}+\boldsymbol{W}_{\mathrm{c}}^{\infty}\boldsymbol{A}^{\mathrm{T}}(\boldsymbol{d}_{\mathrm{a}})=\boldsymbol{B}(\boldsymbol{d}_{\mathrm{a}})\boldsymbol{B}^{\mathrm{T}}(\boldsymbol{d}_{\mathrm{a}}). \tag{12}$$

Notice that $\boldsymbol{W}_{\mathrm{c}}^{\infty}$ is only a function of $\boldsymbol{d}_{\mathrm{a}}$ and does not depend on $\boldsymbol{d}_{\mathrm{c}}$. Furthermore, the minimum control effort needed to achieve a control objective is related to the inverse of the controllability Gramian. Consequently, the scalar function of the controllability Gramian given in Eq. (10) is one good *candidate CPF*. Other candidate CPFs can be found in Refs. [20–23,29–31]. When one solves Eqs. (8) and (9) followed by Eqs. (3) and (4) and obtains the system optimal co-design solution, then the CPF in Eq. (8) is termed a *perfect CPF,* and satisfies certain optimality conditions [10,15,23]. Nevertheless, even when a candidate CPF is not a perfect CPF it can often steer the solution closer to the system optimal co-design solution, as illustrated in the following passive/active car suspension design problem [29]. A detailed discussion of when the CPF approach to optimal co-design should be preferred is given in Ref. [31].

The passive/active suspension design is based upon a 2-degree-of-freedom (i.e., four state) quarter-car model and a linear quadratic optimal control approach [6]. The artifact design variables are the passive suspension stiffness, k_{s}, and damping, c_{s}:

$$\boldsymbol{d}_{\mathrm{a}}=[k_{\mathrm{s}}\quad c_{\mathrm{s}}]^{\mathrm{T}}, \tag{13}$$

while the controller design variables, $\boldsymbol{d}_{\mathrm{c}}$, are the gains of a state feedback controller:

$$\boldsymbol{d}_{\mathrm{c}}=[k_1\quad k_2\quad k_3\quad k_4]^{\mathrm{T}},\ \boldsymbol{u}(t)=-\boldsymbol{d}_{\mathrm{c}}^{\mathrm{T}}\boldsymbol{x}. \tag{14}$$

The objective function for the co-design optimization of this system is

$$J(\boldsymbol{d}_{\mathrm{a}},\boldsymbol{d}_{\mathrm{c}})=J_q(\boldsymbol{d}_{\mathrm{a}},\boldsymbol{d}_{\mathrm{c}})+r_3J_u(\boldsymbol{d}_{\mathrm{a}},\boldsymbol{d}_{\mathrm{c}}), \tag{15}$$

where

$$J_q=\int_0^{\infty}(r_0\dot{x}_4^2+r_1x_1^2+r_{23}^2)\mathrm{d}t,\ J_u=\int_0^{\infty}u^2\mathrm{d}t. \tag{16}$$

The sequential optimization problem is formulated as in Eqs. (1) and (2) with the control gains $\boldsymbol{d}_{\mathrm{c}}=0$ in evaluating J_q and $r_3=J_u=0$. Then given the solution $\boldsymbol{d}_{\mathrm{a}}=\boldsymbol{d}_{\mathrm{a}}^*$, the objective given in Eq. (15) is minimized with respect to $\boldsymbol{d}_{\mathrm{c}}$. The CPF designs are obtained in the same sequential fashion, but using Eq. (8) instead of Eq. (1) in the first step. The candidate CPF, based on the controllability Gramian, is given by Eq. (10). The weights, r_0, r_1, r_2, and r_3, have been selected to be typical of a suspension design for a sporty vehicle [29].

The results of the passive/active suspension design study are given in the Pareto curve in Fig. 3, which shows the trade-off between improved (lower) ride quality and improved (lower) control effort. Note that for a given desired level of the ride quality measure J_q (e.g., 35), the required control effort J_u is much higher (e.g., 2 vs. 1.3) when a sequential design is used instead of a simultaneous (or co-design) approach. Consequently, the co-design achieves the same suspension performance with much less engine power required. Furthermore, note that the CPF designs, with two different weights r_4, lie between the curves for the sequential and co-design cases. Consequently, the candidate CPF selected here improves the design compared to the sequential case, but is not a perfect CPF. Other examples of design using the CPF approach include a MEMS actuator [18,23], which shows an example of a perfect CPF, and a passive/active vibration isolator [49], which shows an extension of Eq. (10) to ease-of-state-estimation as well as ease-of-control by use of a balanced realization such that the controllability and observability matrices of a dynamic system are equal.

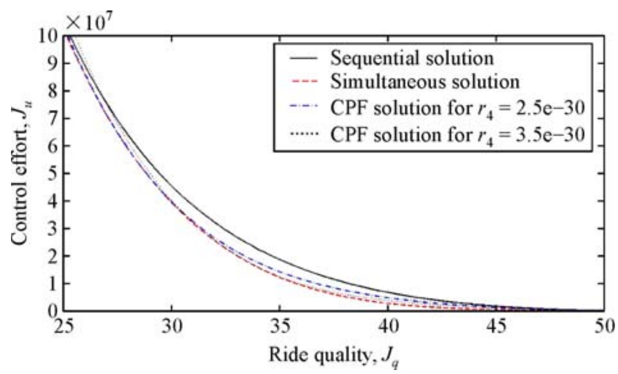


Fig. 3 Pareto curves for the optimal performance of passive/active suspension comparing sequential, simultaneous (co-design) and CPF solutions

3 Controller design for component swapping modularity

Charles Darwin wrote: “It is not the strongest species that survive, nor the most intelligent, but those most responsive to change” [51]. This is not only true for natural systems, but for engineered systems as well. It is desirable to design and build engineered systems that can change as needed in response to external factors, such as consumer preferences, subsystem failures, or the environment in which they operate [52]. One of the keys to engineering such reconfigurable systems is modularity [52]. CSM occurs when two or more basic components are paired with a module, thus creating different product variants belonging to the same product family [53]. In the automotive industry there are over 80 networked microprocessors in today's vehicles, and over 90% of all computer code resides in such embedded systems. There is a need to have different variants of a vehicle depending on the market and to upgrade certain components, without extensive engineering rework. CSM can minimize the need for rework (i.e., calibration and tuning), which can account for as much as 60% of the engineering cost of the control system development process for cars [54].

Consider a feedback control system, as in Fig. 4, with a controller C_{BC}, an actuator A, a plant P, and a sensor S. Traditionally, a feedback control system has two types of communication: Measured plant output from the sensor to the controller (y_{sc}) and a command signal issued by the controller to the actuator (u_{ca}). Assume, however, as in Fig. 4, that part of the control can be distributed to the smart actuator, C_{A}, and sensor, C_{S}. With the bidirectional communication capability of networks, it is now possible to define four additional communication paths among the controller, the "smart" actuator, and the "smart" sensor: (1) Communication from controller to sensor (u_{cs}); (2) communication from actuator to sensor(s) (y_{as}); (3) communication from actuator to controller (y_{ac}); and finally, (4) communication from sensor to actuator (y_{sa}). These additional signal flow paths provide for additional controller design freedom [32,33]. Given a traditional centralized control (i.e., no C_{A}, C_{S}), there is more than one corresponding distributed control in terms of the C_{BC}, C_{A}, and C_{S}. One way of utilizing the new design freedom is to improve component-swapping modularity while ensuring the same performance as for a centralized controller [32,33].

Several methods have been proposed, and demonstrated, for the design of CSM in networked control systems. Existing methods to achieve CSM in network systems include: (1) The 3-Step Method [32–39,41], (2) the Direct Method [36,40,42–45], and (3) a method based on linear matrix inequalities (LMIs) [47,49]. In the 3-Step Method, first, the centralized controller is designed for each system configuration with a different component variant. Then, the order and structure of the distributed controller is assumed, such that only the local controller is tuned when the smart component is swapped. Then, a CSM metric is maximized by exact (or approximate) matching of the transfer function of the distributed controller with that of the centralized controller. The Direct Method, on the other hand, uses a bi-level optimization problem to calculate the distributed controller gains using multidisciplinary design optimization together with a sensitivity analysis of the control signals with respect to the component hardware parameters to establish effective controller distribution. The 3-Step Method is proven to be effective for low order multi-input-multi-output (MIMO) linear systems. However, it is application sensitive and highly reliant on the designer's knowledge of the system and control. Thus, the 3-Step Method is not easy to extend to high order MIMO systems or to nonlinear systems. The Direct Method is much more general in its applicability, but can lead to lengthy computations to achieve a solution. The LMI based approach, approximates the Direct Method for linear MIMO systems and is computationally very efficient.

3.1 Variable cam timing engine [39,41]

In this subsection, the CSM design of a variable-camshaft-timing (VCT) engine is considered (see Fig. 5). VCT is an appealing feature for automotive engines because it allows optimization of the cam timing over a wide range of operating conditions. VCT schemes not only improve fuel economy, but also reduce emissions while improving full load performance. The overall centralized controller for the VCT, shown in Fig. 6, is obtained by using a conventional control design method. Then, for the VCT actuator and exhaust gas oxygen (EGO) sensor components separately, optimal distribution problems are solved, using the 3-Step Method, to find the equivalent distributed controllers and the communication among them. The resulting distributed controllers, shown in Figs. 7 and 8, maximize the CSM of the *smart* VCT unit and the *smart* EGO sensor. The closed-loop response for the distributed CSM designs is indistinguishable from the centralized controller response while providing for swapping of either the smart VCT or the smart EGO components for a practically useful range of module variants [39,41]. The CSM design approach has

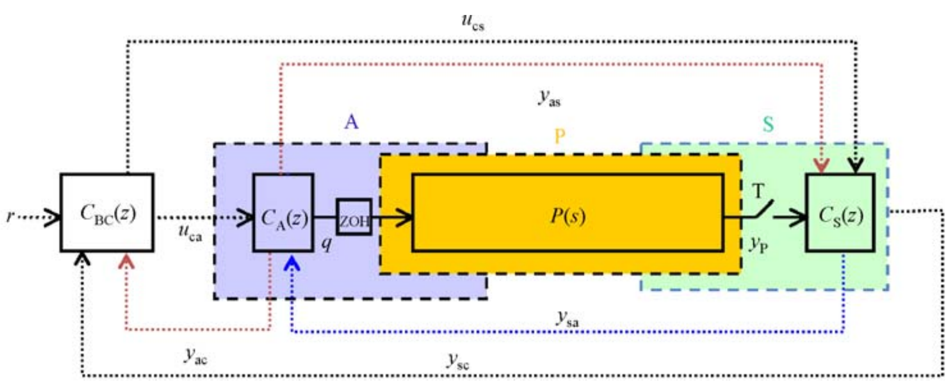


Fig. 4 Bidirectional communication among smart components in a feedback control system

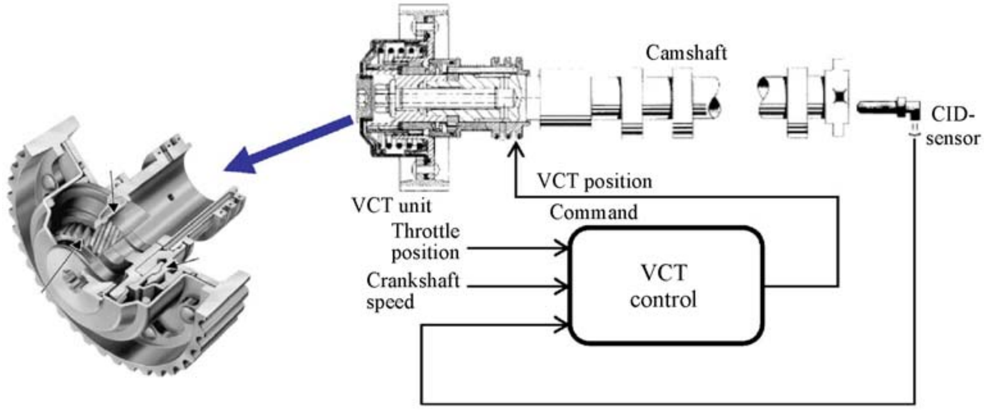


Fig. 5 A VCT system

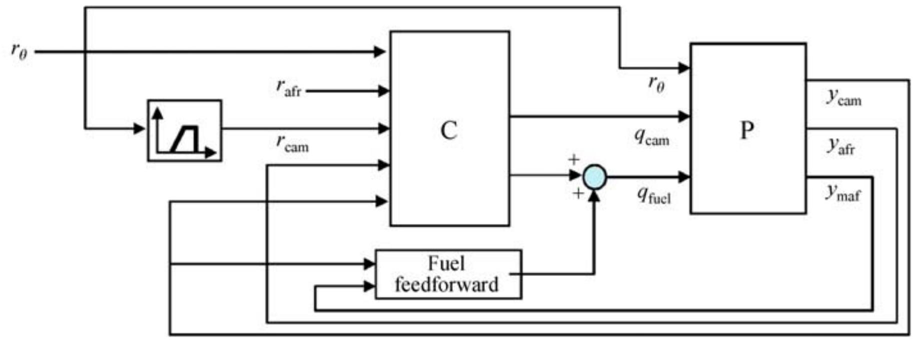
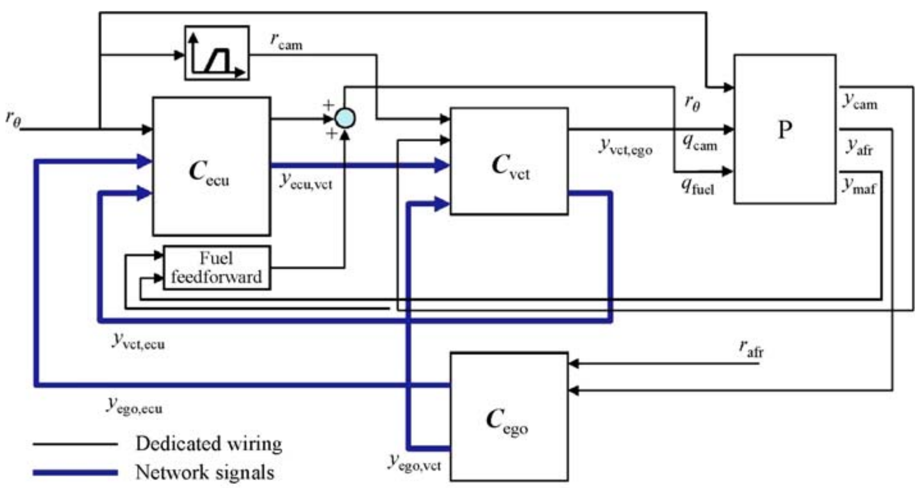


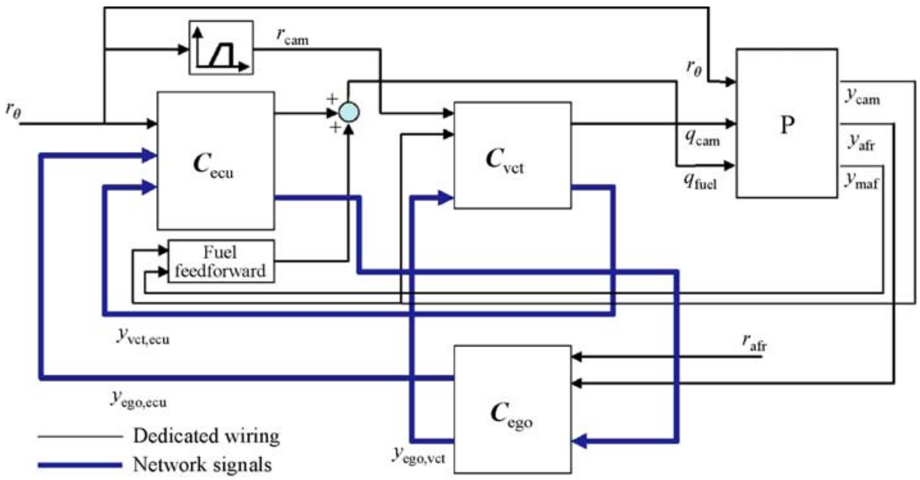
Fig. 6 VCT engine with discrete MIMO centralized controller



$$\boldsymbol{C}_{\rm ecu}(z)=\begin{bmatrix} C_{\rm ecu11} & C_{\rm ecu12} & C_{\rm ecu13} \\ C_{\rm ecu21} & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad \boldsymbol{C}_{\rm vct}(z)=\begin{bmatrix} C_{\rm vct11} & C_{\rm vct12} & 0 & C_{\rm vct14} \\ 0 & 0 & 0 & 0 \\ C_{\rm vct31} & C_{\rm vct32} & 0 & 0 \end{bmatrix}$$

$$\boldsymbol{C}_{\rm ego}(z)=\begin{bmatrix} C_{\rm ego11} & C_{\rm ego12} & 0 & 0 \\ C_{\rm ego21} & C_{\rm ego22} & 0 & 0 \end{bmatrix}$$

Fig. 7 Controller distribution to maximize VCT actuator modularity



$$C_{ecu}(z) = \begin{bmatrix} C_{ecu11} & C_{ecu12} & C_{ecu13} \\ 0 & 0 & 0 \\ C_{ecu21} & 0 & 0 \end{bmatrix} \qquad C_{vct}(z) = \begin{bmatrix} C_{vct11} & C_{vct12} & 0 & C_{vct14} \\ 0 & 0 & 0 & 0 \\ C_{vct31} & C_{vct32} & 0 & 0 \end{bmatrix}$$

$$C_{ego}(z) = \begin{bmatrix} C_{ego11} & C_{ego12} & 0 & 0 \\ C_{ego21} & C_{ego22} & 0 & C_{ego24} \end{bmatrix}$$

Fig. 8 Controller distribution to maximize EGO sensor modularity

also been successfully applied to a DC motor control [37], to control of a swappable throttle actuator for idle speed control [36,40] and has been experimentally validated for a modular *x*-*y* table [46,50]. In the next subsection the CSM controller design for a plug-in-hybrid electric vehicle (PHEV) is discussed.

3.2 Plug-in hybrid electric vehicle [42,43,45]

Consider the CSM design of a series PHEV to achieve battery CSM. The goal is to enable swapping between two or more battery modules, while ensuring that the controller achieves the best possible fuel efficiency within battery state-of-charge (SOC) limits. The smart battery component becomes swappable if the battery change can be accommodated by only recalibrating the controller built inside the battery module so that the vehicle meets the same performance achievable by redesigning the entire centralized controller. The swappable battery, thus, becomes a plug-and-play component. The centralized design of a supervisory controller (i.e., before a CSM design) is shown schematically in Fig. 9. The supervisory controller (SC) ensures that desired power command, $P_{w,cmd}$, is delivered to the wheels, P_w, within specifications while minimizing fuel consumption by and ensuring the battery SOC is maintained within specifications. This is accomplished by sending appropriate power command, $P_{e,cmd}$ and $P_{b,cmd}$, to the engine and battery, respectively. The controller has gains, which are determined by the specifications, as well as the parameters of the model of the dynamic system. One of those parameters is the battery size parameter, B_s, which changes if the battery unit (BAT) is swapped to accommodate different all-electric-ranges for different customer commuting distances.

The CSM design for the same PHEV is schematically illustrated in Fig. 10, where the centralized SC has been distributed to a vehicle supervisory controller (VSC) in the vehicle, and to a battery supervisory controller (BSC), which resides in the swappable smart battery unit. The VSC and BSC are designed by the Direct Method, using a bi-level optimization approach and a sensitivity analysis. The design ensures that only the controller gains for the BSC need to be recalibrated when the battery parameter, B_s, changes. The controller gains in the VSC remain

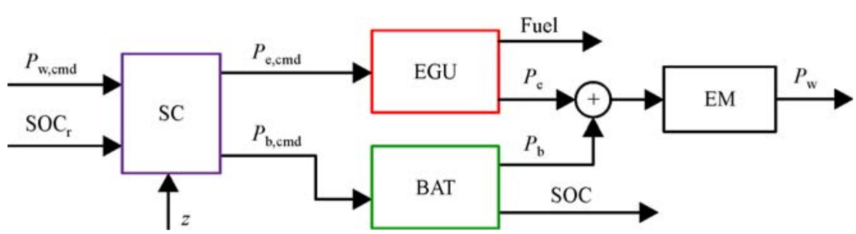


Fig. 9 The PHEV centralized supervisory controller (SC) for the engine and generator unit (EGU), battery (BAT), and electric motor (EM)

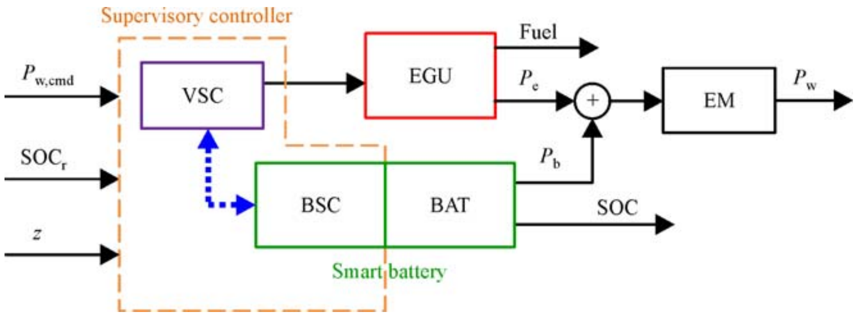


Fig. 10 The PHEV distributed supervisory controller to achieve CSM with a vehicle supervisory controller (VSC) in the vehicle, and a battery supervisory controller (BSC) as part of the smart battery module

unchanged, and do not need to be recalibrated, when a battery module is swapped. The results for fuel economy and SOC in Table 1 show that, for 4 different values of B_s (i.e., 4 different battery modules), the CSM designs provide exactly the same fuel economy as the centralized controller provides in each case, while maintaining SOC within 10% of the desired value. Consequently, battery CSM is achieved without compromising fuel economy.

Table 1 Performance comparison of distributed CSM control to centralized control

Battery parameter, B_s	Same fuel economy as centralized controller?	Battery SOC within 10% of centralized controller?
1.29×10^{-5}	Yes	Yes
1.71×10^{-5}	Yes	Yes
2.57×10^{-5}	Yes	Yes
5.14×10^{-5}	Yes	Yes

4 Summary, conclusions and future work

Automobiles have rapidly become complex systems which integrate mechanical and electronic components through intelligent software control (e.g., autonomous driving, electric/hybrid powertrains, brake-by-wire, steer-by-wire, lane keeping, parking assist, and many others). This paper reviews two recent methods for the design of mechatronic systems, or smart products, and highlights their applications to problems in automotive control. First the combined design, or *co-design*, of a smart artifact and its controller is considered [7–31]. It is shown that the combined design of an artifact and its controller can lead to improved performance compared to sequential design (i.e., design the artifact first, then design its controller). The coupling between the artifact and controller design problems is quantified, and methods for co-design are presented. The CPF method, which provides for ease of design as in the sequential approach but approximates the performance of the co-design approach, is highlighted with application to the design of a passive/active automotive suspension. Second, to ensure responsiveness to change with plug-and-play components, the design for CSM of a distributed controller for a smart product is discussed [32–50]. CSM is realized by employing distributed controllers residing in networked smart components, with bidirectional communication among components over the network. Several approaches to CSM design are presented and discussed. Applications of the method to a variable-cam-timing engine, and to enable battery swapping in a plug-in hybrid electric vehicle, are highlighted.

While the co-design and CSM methods reviewed here have clear and quantifiable benefits, they are just a start in terms of engineering methods needed for the design of smart products. One can envision future research that will be needed to achieve optimal co-design not only of two (i.e., artifact and control) but of multiple subsystems (e.g., vehicle suspension design with passive/active components at each wheel). Similarly, CSM design will be needed for multiple swappable components (e.g., swappable EGO sensor and VCT actuator and throttle actuator in a VCT engine). Furthermore, one can envision the need to combine co-design and CSM methods to achieve modular system optimal design (e.g., modular passive/active suspension modules for vehicle variants). We have only scratched the surface of this research frontier, and many exciting research topics remain.

Acknowledgements The author is pleased to acknowledge the collaborators on this research, i.e., Profs. P.Y. Papalambros and I.V. Kolmanovsky, as well as Drs. J. Reyer, H.K. Fathy, S.F. Alyaqout, D.L. Peters, M. Çakmakcı, S. Li and A. Ghaffari. The research featured in this article was sponsored by the National Science Foundation, the U.S.A. Army Automotive Research Center, the Ford Motor Company, and United Technologies, Inc.

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