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Intelligent Motion Control for Electromechanical Servos Using Evolutionary Learning and Adaptation Mechanisms

Sergey Edward Lyshevski[1] and **Michael G. Safonov**[2]

[1]Department of Electrical and Computer Engineering
Purdue University at Indianapolis, Indianapolis, Indiana 46202-5132
E-mail: lyshevs@engr.iupui.edu

[2]Department of Electrical Engineering—Systems
University of Southern California, Los Angeles, California 90089-2563
E-mail: msafonov@usc.edu

Abstract

Electromechanical servos integrate servomotors, power converters, sensors, integrated circuits, and controllers. In conventional applications, analog and digital proportional-integral-derivative controllers are widely used, and electric servomotors can be straightforwardly controlled by making use of the electromagnetic and energy conversion phenomena. High-performance servos must be designed to achieve specified criteria and standards in expanded operating envelopes. These requirements can be guaranteed implementing advanced control algorithms designed applying novel control methods. This paper stresses the need to design intelligent systems to solve the intelligent motion control problem. It must be emphasized that in general, motion control cannot be viewed merely as robust tracking control because in addition to accuracy, stability and disturbance attenuation, other criteria (e.g., efficiency, reliability, noise, vibration, and electromagnetic interference) and tasks (e.g., decision making, intelligence, diagnostics, and health monitoring) must be performed. Intelligent motion control can be achieved by implementing learning and adaptation mechanisms (through evolutionary learning, reconfiguration, rescheduling, tuning, and optimization) with the ultimate objective being to attain the optimal overall performance. The performance (objective) functional is evaluated using measured control, reference, and output vectors that are the system performance variables. It is demonstrated that using the evolutionary learning and adaptation, the intelligent motion control problem can be solved without linguistic or mathematical models of electromechanical servos. In particular, unfalsified and *premium* control laws are designed, and experimental results are documented.

1. Introduction

For complex dynamic systems, to solve optimization problems, a variety of concepts have been devised and applied [1]. Generally, these methods rely to some extent on prior knowledge of plant and noise models. But, there are cases involving systems operating in dynamic environments under uncertainties where it can be difficult to develop sufficiently reliable mathematical models. In these cases, model-based optimization exhibits well-known difficulties and drawbacks. For such particularly challenging cases, it is preferable to design controllers that consistently and reliably exhibit evolutionary learning and adaptation capabilities. To achieve this goal, one needs data-driven intelligent design concepts and tools that rely primarily on the logical implications of experimental evidence, rather than on prior knowledge of model structures and statistical properties. One such technique is provided by the unfalsified control theory [2]. Other viable procedures are based upon neural networks [3].

In this paper we develop a method in which unfalsified performance is optimized with respect to available experimental evidence. In this approach, linear and nonlinear maps of the system performance variables (control, reference, and output vectors) are used for real-time controller synthesis that minimizes sensor-data driven objective functionals. Specifically, we use the unfalsification criteria to sift candidate controllers to design — and to implement at each time — a *premium controller*, which by definition, given in this paper, is a controller whose unfalsified performance level is optimal (superior) with respect all available past experimental evidence. In this manner, we design an intelligent servo that learns and optimizes the system performance by adapting and reconfiguring controllers and tuning feedback coefficients based on the unfalsified – *premium* control paradigm. The input and output variables are defined from the set of the system performance variables (measured information set) that allow one to synthesize the objective functional to evaluate the performance status directly from the sensed sensor data. Making use the objective functional, the specified (desired) performance, as well as the measured information set, one can design the unfalsified control algorithms and find the *premium* controller. From implementation standpoints, these tasks can be implemented using neural networks. The *controller optimizer* and the *feedback gain optimizer* are synthesized and implemented. Real-time learning, adaptation, reconfiguration, and optimization are achieved by minimizing the objective functional.

The solution of the tracking control problem for servo-systems is straightforward [4-6]. The actual linear displacement L (output) is compared with the reference displacement L_{ref}. Using the tracking error $e(t) = L_{ref}(t) - L(t)$, the analog or digital controller calculates the control signals based upon the control law implemented and feedback coefficients set.

Brushless permanent-magnet synchronous machines, which are efficient, reliable, and have high torque density, are widely used in servos and drives [4]. Therefore, the studied high-performance servo is actuated by the permanent-magnet synchronous motor. The power amplifier is used to regulate the magnitude of the applied voltages u_{as}, u_{bs} and u_{cs} supplied to the phase windings. The frequency of the phase voltages applied is related to the rotor displacement measured by the Hall sensors. Compared with the existing solutions in control of servos, in addition to the tracking error $e(t)$, servo-motor and power amplifier efficiencies, as well as accuracy and settling time are used as the performance variables. The block-diagram of an intelligent closed-loop system is illustrated in Figure 1.

In intelligent servos, to calculate the PWM signals which drive the high-frequency transistors of power amplifiers, the control laws and the feedback coefficients must be found and set through the evolutionary learning and adaptation mechanisms. Designing the *controller optimizer* and the *feedback gain optimizer*, we optimize the servo performance, and evolutionary learning and adaptation mechanisms are applied. The *controller* and *feedback gain optimizers* are implemented using the multi-layer neural networks.

It must be emphasized that the intelligent motion control problem is much more complex task compared with the robust tracking control. In particular, in addition to the tracking error, control and sensor data, as well as events and performance variables, are used to synthesize intelligent high-performance servos.

2. Unfalsified and *Premium* Control Laws: Optimization, Learning, and Adaptation

In general, performance goals, controllers, and controlled systems are relations between control (u), reference (r), and measured outputs (y). Using the triple (r, y, u) one can synthesize objective functionals and qualitatively analyze the system performance. We denote by R, Y and U the universal sets of conceivable values for each of these signals. Thus, the closed-loop response triples are $(r, y, u) \in R \times Y \times U$.

In unfalsified control theory [2], one evaluates control laws $u=K(r,y)$ using a performance objective functional $J_F : R \times Y \times U \to \Re$ and defines a performance goal as $J_F(r, y, u) \le \gamma, \forall r \in R$.

A desired performance level $\gamma \in \Re$ is achieved if, for all input signals $r \in R$, the corresponding closed-loop response triples (r, y, u) lie in the set

$$J_S(\gamma) \stackrel{\Delta}{=} \{(r, y, u) \in R \times Y \times U \mid J_F(r, y, u) \le \gamma\}.$$

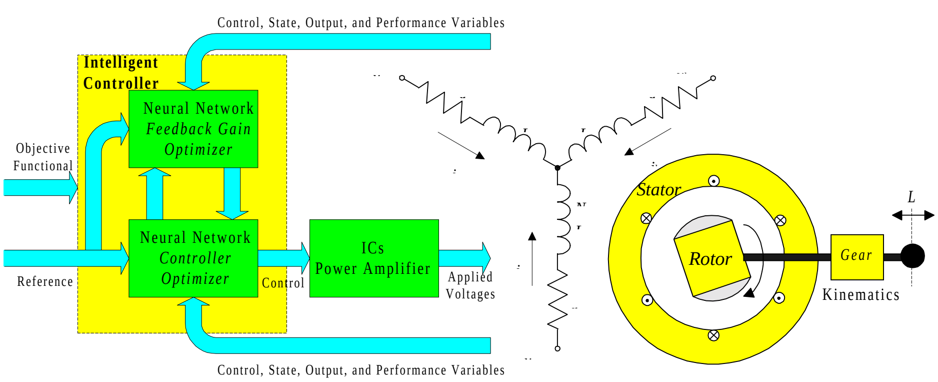

Figure 1. Servo with the intelligent controller

Definition 1. A controller $u=K(r,y)$ is said to be falsified with respect to performance level γ if the measurement data $\{(u_{data}(t), y_{data}(t) \mid t \in T\}$ is sufficient to deduce that the controller $u=K(r,y)$ cannot satisfy the performance goal $J_F(r,y,u) \le \gamma, \forall r \in R$. Otherwise the controller $u=K(r,y)$ is said to be unfalsified.

Definition 2. A controller $u=K(r,y)$ that is unfalsified with respect to the performance level γ is said to be *premium* and denoted K_p if there is no other controller that is unfalsified with respect to lesser performance level.

It must be emphasized that the controllers of the general form $u=K(r,y)$ considered here include tracking control laws having as their input the error

$e(t) = r(t) - y(t)$.

It is evident that the system performance is measured by the system performance variables. That is, the performance (e.g., accuracy, controllability, efficiency, effectiveness, losses, et cetera) is the nonlinear map as given by $p = f(u, r, y)$.

Our goal is to synthesize the unfalsified and *premium* controllers. Using the discussions given, we may order controllers according to their unfalsified performance level γ using the following theorem.

Theorem 1. A controller $u=K(r,y)$ is unfalsified with respect to performance level γ if and only if for each triple $(r_0, y_0, u_0) \in M_S \cap K_S$ there exists at least one pair (y_1, u_1) satisfying

$(r_0, y_1, u_1) \in M_S \cap K_S \cap J_S(\gamma)$,

where

(1) $J_S(\gamma) \overset{\Delta}{=} \{(r,y,u) \in R \times Y \times U \mid J_F(r,y,u) \le \gamma\}$

(2) $M_S \overset{\Delta}{=} \{(r,y,u) \in R \times Y \times U \mid u(t) = u_{data}(t),\ y(t) = y_{data}(t),\ \forall t \in T\}$,

(3) $K_S \overset{\Delta}{=} \{(r,y,u) \in R \times Y \times U \mid u = K(r,y)\}$.

Three sets $J_S(\gamma)$, M_S and K_S are called the *performance specification, measurement data* and *controller* sets, respectively.

The definition of the set M_S is based on the observation that the data are partial characterizations of points on the ‘graph’ of the plant. Any correct model of the plant must be capable of exhibiting behavior consistent with the observed data, which is to say that the model must include behaviors that *interpolate* the observed data.

The set M_S consists by definition of those closed-loop response triples $(r,y,u) \in R \times Y \times U$ such that the pair $(u(t), y(t))$ interpolates the observed data $(u_{data}(t), y_{data}(t))$.

The set K_S denotes the graph of a particular candidate controller $u=K(r,y)$, which is a subset of $R \times Y \times U$. The set of candidate controllers is denoted by K, and K is not a subset of $R \times Y \times U$.

The conditions of Theorem 1 relaxed when the dependence of the performance objective functional $J_F(r,y,u)$ on the values of (y,u) is determined entirely by the data $\{(u_{data}(t), y_{data}(t) \mid t \in T\}$ [7, 8]. In this case, the ‘truncated space’ simplification of the unfalsified control theorem holds.

The *premium* controllers can be designed using the following results.

Theorem 2. A controller $u=K(r,y)$ is unfalsified with respect to performance level γ if and only if

(4) $M_S \cap K_S \cap \overline{J_S(\gamma)} = \varnothing$,

where $\overline{J_S(\gamma)}$ is the complement of the set $J_S(\gamma)$.

The *premium* controller and its performance level γ_{opt} are found by solving the following optimization problem

(5) $$\gamma_{\text{opt}} = \min_{K \in \mathsf{K}} \gamma \quad \text{subject to } M_S \cap K_S \cap \overline{J_S(\gamma)} \ne \varnothing$$

where K is the set of candidate controllers.

The performance level γ_{opt} depends on three variables: the measured input and output data $(u_{data}(t), y_{data}(t))$, the candidate controller set, and the real performance objective functional $J_F(r,y,u)$ in $R \times Y \times U$.

It should be emphasized that when the objective functional is given, the performance level γ_{opt} is a function only of $(u_{data}(t), y_{data}(t))$ and the candidate controller set.

By Definition *2*, the *premium* controller K_p is a member of the set K that achieves minimum in (5).

The elements of set $\overline{J_S(\gamma)}$ are triples (r,y,u) that violate the performance specification

$$J_S(\gamma) \overset{\Delta}{=} \{(r,y,u) \in R \times Y \times U \mid J_F(r,y,u) \le \gamma\}.$$

That is,

$$\overline{J_S(\gamma)} \overset{\Delta}{=} \{(r,y,u) \in R \times Y \times U \mid J_F(r,y,u) > \gamma\}.$$

Thus, Theorem 2 says that a controller is unfalsified if and only if there are no closed-loop response triples (r,y,u), consistent with both the controller relation K_S and the measurement data, that violate the performance specification.

Recalling that $e(t) = r(t) - y(t)$, the nonquadratic objective functionals, which penalize the system dynamics with respect to the control, output, and error vectors, can be found as [6]

$$J_F(u,y,e) = \int_{t_0}^{t_f} \sum_{i=0}^{\varsigma} \left[\left(u^{\frac{i+\beta+1}{2\beta+1}} \right)^T Q_{Ui} u^{\frac{i+\beta+1}{2\beta+1}} + \left(y^{\frac{i+\beta+1}{2\beta+1}} \right)^T Q_{Yi} y^{\frac{i+\beta+1}{2\beta+1}} + \left(e^{\frac{i+\beta+1}{2\beta+1}} \right)^T Q_{Ei} e^{\frac{i+\beta+1}{2\beta+1}} \right] dt,$$

where $Q_{Ui} \in \mathbb{R}^{m \times m}$ and $Q_{Yi} \in \mathbb{R}^{n \times n}$ and $Q_{Ei} \in \mathbb{R}^{b \times b}$ are the diagonal weighting matrices; ζ and β are the nonnegative integers, ζ=0, 1, 2,..., and β=0, 1, 2,...

One can readily use this objective functional. For example, the well-known quadratic functional

$$J_F(u,y,e) = \int_{t_0}^{t_f} \left(u^T Q_{U0} u + y^T Q_{Y0} y + e^T Q_{E0} e \right) dt$$

is found by letting $\zeta = \beta = 0$.

Using ζ=1 and β=0, one obtains nonquadratic objective functional

$$J_F(u,y,e) = \int_{t_0}^{t_f} \left(u^T Q_{U0} u + u^{2^T} Q_{U1} u^2 + y^T Q_{Y0} y + y^{2^T} Q_{Y1} y^2 + e^T Q_{E0} e + e^{2^T} Q_{E1} e^2 \right) dt.$$

Another, more general form of the objective functional is

$$J_F(u,x,e) = \int_{t_0}^{t_f} \left[\sum_{i=0}^{\varsigma} \left(u^{\frac{i+\beta+1}{2\beta+1}} \right)^T Q_{Ui}(t) u^{\frac{i+\beta+1}{2\beta+1}} + \sum_{i=0}^{\eta} \left(y^{\frac{i+\gamma+1}{2\gamma+1}} \right)^T Q_{Yi}(t) y^{\frac{i+\gamma+1}{2\gamma+1}} + \sum_{i=0}^{\sigma} \left(e^{\frac{i+\chi+1}{2\chi+1}} \right)^T K_{Ei}(t) e^{\frac{i+\chi+1}{2\chi+1}} \right] dt,$$

where ζ, β, η, γ, σ and χ are the nonnegative integers.

The controllers can be designed by examining different control laws K in the candidate controller set $\mathbf{K}$, eliminating K which do not satisfy the objective functional, and tuning the feedback gains.

A prearranged "robust" control law with feedback gains which ensure stability in the worst-case scenario can be used to initialize the learning and adaptation process. That is, to guarantee the stability, the search starts in the chosen initial set of control laws and in the specified feedback coefficients interval (for example, it is no need to perform the search using positive feedback gains).

In this paper, the real-time learning and adaptation with reconfiguration and tuning are performed using neural networks. The proposed neural networks-based closed-loop system has advantages over other configurations due to the application of two neural networks; see Figure 1. In particular, the *controller optimizer* searches, adapts, and reconfigures the control laws (with ultimate objective to find unfalsified and *premium* controllers), while the *feedback gain optimizer* tunes the feedback coefficients. These *optimizers* are implemented to perform real-time learning, adaptation, reconfiguration, scheduling, and optimization based upon input-output mappings and objective functionals. To synthesize these input-output mappings, the events and system performance variables are applied.

The neural networks architecture is synthesized using two building blocks. These two three-layer neural networks (*controller optimizer* and *feedback gain optimizer*) are synthesized, and multi-input/multi-output neuron output is given by

$$u_3 = f_3 \left[W_3 f_2 \left(W_2 f_1 \left(W_1 v + B_1 \right) + B_2 \right) + B_3 \right],$$

where u_3 is the output vector, $u_3 \in \mathbb{R}^m$; f is the nonlinear function; W_i are the weighting matrices; v is the input vector (performance variables), $v \in \mathbb{R}^k$; B_i are the bias vectors. The corresponding subscripts 1, 2 and 3 are used to denote the layer variables.

The events and performance variables from the input layer are fed into the hidden layer. This solution guarantees stability, minimizes the error in the output layer, as well as ensures the filtering capabilities.

It should be emphasized that W_i and B_i are adjusted through the training (learning) providing the evolutionary adaptation mechanism. To approximate the unknown functions, weighting matrices and the bias vectors are determined, and the selection of W_i and B_i is performed using the backpropagation method. Applying the gradient descent optimization procedure, one minimizes a mean square error performance index using the end-to-end neural network behavior. Using the inputs vector v and the output vector z, $z \in \mathbb{R}^k$, the quadratic performance functional is

$$J=\sum_{j=1}^{p}\left(z_j-u_j\right)^T Q\left(z_j-u_j\right)+\alpha\sum\left(w_{i,j}^k\right)^2$$
$$=\sum_{j=1}^{p}\varepsilon_j^T Q\varepsilon_j+\alpha\sum\left(w_{i,j}^k\right)^2,$$

where $\varepsilon_j = z_j - u_j$ is the error vector; $Q\in \mathbb{R}^{p\times p}$ is the diagonal weighting matrix; α is the regularization parameter.

The steepest descent algorithm is applied to approximate the mean square errors, and the learning rate and sensitivity are studied for the quadratic performance functional. In particular, the stability and convergence are examined using the Lyapunov theory. Taking note of the optimal weight W_{opt}, we define $\Delta W = W_{opt} - W$. The quadratic candidate $V(\varepsilon,\Delta W)=\frac{1}{2}\varepsilon^T Q_e\varepsilon+\frac{1}{2}\Delta W^T Q_W\Delta W$ is examined to find the adaptation gains.

3. Unfalsified and *Premium* Controller Design: Evolutionary Learning – While – Controlling

To actuate the servomechanism, we used the Kollmorgen permanent-magnet synchronous servomotor H-232 (135 W, 434 rad/sec, 40 V (*rms*), 0.42 N-m, 6.9 A) controlled by the PWM power amplifier. The voltages, applied to the *as*, *bs* and *cs* motor windings are displaced by 120 electrical degrees, and the Hall sensors are used to measure the rotor angular displacement. The magnitude of the applied voltages is controlled by regulating the power amplifier duty ratio. That is, the controller output PWM signals drive the MOSFETs gate drivers [4].

In addition to the tracking accuracy, minimum settling time, stability, and disturbance attenuation, the servo-system efficiency is maximized by minimizing the electrical and mechanical losses. To attain real-time learning and adaptation, two neural networks (*controller optimizer* and *feedback gain optimizer*) are trained to find unfalsified control laws, as well as to derive the *premium* controller with optimal feedback coefficients based upon the best fit (minimum value of the objective functional), estimated by the to performance level γ, through learning, adaptation, and reconfiguration.

The objective functional, which measures the servo performance, must be synthesized using the power amplifier duty ratio (d_D, $u = d_D$), currents in the motor windings (i_{as}, i_{bs} and i_{cs}), angular velocity (ω_{rm}), and tracking error, $e(t)=L_{ref}(t)-L(t)$.

In particular, we synthesize

(6)

$$J_F(u,y,e)=\underbrace{\min_{i_{as},i_{bs},i_{cs}}\int_{t_0}^{t_f}\begin{bmatrix} i_{as} & i_{bs} & i_{cs}\end{bmatrix}\begin{bmatrix} i_{as}\\ i_{bs}\\ i_{cs}\end{bmatrix}dt}_{\text{efficiency}}+\underbrace{\min_{\omega_{rm}}\int_{t_0}^{t_f}\omega_{rm}^2 dt}_{\text{efficiency}}$$
$$+\underbrace{\min_{t,e}\int_{t_0}^{t_f}\left(1+t\left|e\right|\right)dt}_{\text{dynamics (minimum-time)}}+\underbrace{\min_{d_D,e}\int_{t_0}^{t_f}\left(d_D^2+100e^2+10e^4\right)dt.}_{\text{dynamics (control and error transient behavior)}}$$

This nonquadratic objective functional is synthesized using four integrals (terms). In particular, the first and second terms maximize the servo efficiency penalizing the magnitude of the phase currents and angular velocity. The third and fourth integrals provide the desired transient behavior penalizing the transient time (minimum-time problem), control, and tracking error.

Applying the closed-loop response triple (r,y,u), one has the input-output mapping. This mapping is used in learning, adaptation, reconfiguration, scheduling, and optimization to attain the ultimate goal, e.g., optimize the overall servo performance. The control laws are searched and adapted in the subset of control laws (linear quadratic regulator, proportional-integral-derivative, nonlinear, robust, and relay controllers) by the *controller optimizer*. Solving the minimization problem, the feedback gains are found within the assigned feedback coefficient intervals by the *feedback gain optimizer*. The negative feedback coefficients are set to prevent the search in the unstable and sensitive domains. Two neural networks (*controller optimizer* and *feedback gain optimizer*) are trained. The *controller optimizer* defines the control law based upon the best fit and optimal overall performance minimizing the performance functional, and the *feedback gain optimizer* searches for the feedback coefficients to be implemented. Thus, we implement an evolutionary learning-while-controlling concept.

To perform the search, the candidate controller set K is assigned. In particular, linear and nonlinear proportional-integral-derivative controllers with state feedback, linear quadratic, integral quadratic, and relay-type control algorithms form the set of controllers.

Integral, linear quadratic, and relay-type controllers do not satisfy the performance level γ as estimated using the objective functional (6). Thus, these control laws are falsified, and must be eliminated. The unfalsified controller was obtained as the nonlinear proportional-integral-derivative controller with state feedback in

$$u = \text{sat}_{-1}^{+1}\left(k_{e1}e + k_{e2}e\left| e \right| + k_{e3}e^3 + k_{e4}\int edt - k_{\omega}\omega_{rm} - k_i \begin{bmatrix} i_{as} \\ i_{bs} \\ i_{cs} \end{bmatrix} \right)$$

Using the objective functional (6)and solving the optimization problem (5), the *premium* control law, which optimizes the overall performance, is found. It must be emphasized that the control (duty ratio) is bounded by ± 1. The dynamics of an intelligent servo is shown in Figure 2 for the following command displacement $r(t) = \begin{cases} 0.25 \text{ m}, & t \in [0 \;\; 0.06] \text{ sec} \\ 0.125 \text{ m}, & t \in (0.06 \;\; 0.1] \text{ sec} \end{cases}$.

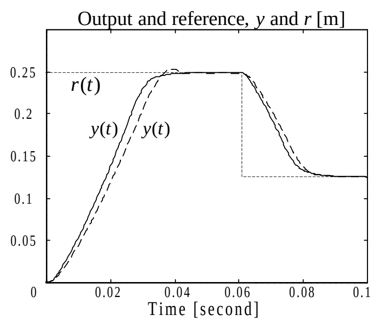

Figure 2. Dynamics of the intelligent servo

The feedback gains of the *premium* control are found in real-time through adaptation, and at *t*=0.1 sec

$$u(t) = \text{sat}_{-1}^{+1}\left(3.9e + 0.7e\left| e \right| + 0.58e^3 + 2.4\int edt - 0.05\omega_{rm} - [0.1 \;\; 0.1 \;\; 0.1] \begin{bmatrix} i_{as} \\ i_{bs} \\ i_{cs} \end{bmatrix} \right)$$

The analysis of the transient behavior illustrates that the steady-state error is zero, and the settling time is 0.04 sec. Adaptation and reconfiguration are studied because the servo operates in a dynamic environment due to different load torques, variation of temperature, etc. In fact, the servomotor and power amplifier parameters vary due to temperature changes. We study the servo-system in the temperature range from 25°C to 100°C. Figure 2 illustrates the servo behavior if the temperature is 25°C (solid line). The rotor resistance increases and the susceptibility decreases with increasing temperature. The electromagnetic motor torque decreases as temperature rises. The parameters of the power converter also vary due to the temperature variations. These phenomena with the corresponding degradation of dynamics are conformed during the experiments, see Figure 2 (the output dynamics for 100°C is given by the dashed line). However, through learning and adaptation, the *premium* controller maintains the same settling time (minimum-time dynamics), zero error, and high efficiency despite of parameter variations.

4. Conclusions

Servo-systems, which integrate servo-motors, power amplifiers, integrated circuits, sensors, and mechanical coupling, exhibit nonlinear dynamics, and it is difficult to model this complex behavior using physical laws. In this paper, the intelligent motion control problem was solved, and intelligent servos were designed using evolutionary learning and adaptation mechanisms based on the *premium* control paradigm. These intelligent servos can be implemented using neural networks implementing evolutionary learning-while-controlling setup. Based on the unfalsified control paradigm, *controller* and *feedback gain optimizers* were synthesized. The concept reported was shown to provide a promising approach to problems and inconsistencies in modeling, analysis, and design of complex systems. To illustrate the results, we designed an intelligent servo that learns and optimizes the system performance by adapting and reconfiguring controllers and setting optimal feedback coefficients. The *premium* controller was designed and tested.

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