AUTOMATING CONTROL SYSTEM DESIGN VIA A MULTIOBJECTIVE EVOLUTIONARY ALGORITHM

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This chapter presents a performance-prioritized computer aided control system design (CACSD) methodology using a multi-objective evolutionary algorithm. The evolutionary CACSD approach unifies different control laws in both the time and frequency domains based upon performance satisfactions, without the need of aggregating different design criteria into a compromise function. It is shown that control engineers' expertise as well as settings on goal or priority for different preference on each performance requirement can be easily included and modified on-line according to the evolving trade-offs, which makes the controller design interactive, transparent and simple for real-time implementation. Advantages of the evolutionary CACSD methodology are illustrated upon a non-minimal phase plant control system, which offer a set of low-order Pareto optimal controllers satisfying all the conflicting performance requirements in the face of system constraints.

1. Introduction

With rapid developments in linear time-invariant (LTI) control theories and algorithms in the past few decades, many control schemes ranging from the most straightforward proportional plus integral plus derivative (PID), phase lead/lag and pole-placement schemes to more sophisticated optimal, adaptive and robust control algorithms have been available to control engineers. Each of these control schemes, however, employs a different control characteristic or design technique that is often restricted ad-hoc to one particular problem or addresses only a limited subset of performance issues. To design an optimal controller using these methods, control engineers need to select an appropriate control law that best suits the application on hand, and to determine a practical control structure with a set of optimal controller parameters that best satisfies the usually conflicting performance specifications in both the time and frequency domains.

An effective design approach is to coin the linear controller synthesis by meeting all types of performance requirements and constraints via numerical optimization, instead of by a specific control scheme or in a narrow problem domain. This approach of simultaneously addressing design specifications in both the time and frequency domains is, however, semi-infinite and generally not everywhere differentiable[1-6]. Therefore conventional numerical approaches that often rely on a smooth and differentiable performance index can only address a small subset of the problem or to limit the type of the design specifications for convex optimization[7-8], which forms the major obstacle on the development of a generalized numerical optimization package for practical control applications.

In this chapter, a uniform CACSD methodology is presented to accommodate LTI control laws based on performance requirements and practical design constraints in both the time and frequency domains, without the need of linear parameterization or confining the design in a particular domain for convex optimization. Unlike existing mutually independent and individual LTI control schemes, control engineers can easily address practical performance requirements such as rise time or overshoots in the time domain, and formulate the robustness specifications such as disturbance rejection or plant uncertainty according to the well developed robustness theorems in the frequency domain, as desired.

Developing such an optimal ULTIC system, however, requires a powerful and global multi-objective optimization technique to determine the multiple controller parameters simultaneously, in order to satisfy a set of usually conflicting design specifications in a multi-modal multi-objective design space. Complexity, nonlinearity and constraints in practical systems, such as voltage/current limits, saturation, transportation delays, noise or disturbance, cause the design problem space to be discontinuous and difficult to solve using conventional analytical or CACSD software packages. Current numerical methods employed in existing CACSD tools are based upon *a-priori* gradient-guided approaches, which are often applicable to a subset of design problem or only useful for control system analysis and simulations[2, 3]. These tools are computationally intractable because in the worst case their computation time grows exponentially with the number of design parameters. They are incapable of delivering a global, high-dimensional and automated multi-objective design solution in designing an optimal ULTIC system. Since practical design specifications and constraints are often mixed or competing among each other, using such a CACSD package for optimal ULTIC designs often requires control engineers to go through numerous heuristic simulations and analysis before a 'satisfactory' design emerges.

The simulation and analytical power of modern CACSD can, however, be utilized to achieve design automation of ULTIC systems if it is interfaced and coupled with powerful evolutionary based intelligent search tools. Sedgewick[9] pointed out that one way to extend the power of a digital computer is to endow it with the power of intelligent non-determinism to assert that when an algorithm is faced with a choice of search options, it has the power to intelligently 'guess' for the right one. Artificially emulating Darwinian's principle of 'survival-of-the-fittest' on natural selection and genetics[10], evolutionary algorithm is such a non-deterministic polynomial (NP) computing technique that has the ability to replace human 'trial-and-error' based iterative process by intelligent computer-automated designs. Using such an evolutionary design optimization approach, control engineers' expertise can also be easily incorporated into the initial design 'database' for intelligent design-reuse to achieve a faster convergence[11]. More importantly, such an evolutionary CACSD approach allows any mixed or sophisticated conflicting specifications and constraints in practical applications be unified and addressed easily under one design banner: *Performance Satisfaction*.

This chapter presents an MOEA application to CACSD design automation in ULTIC systems by unifying all LTI approaches under performance satisfactions in both the time and frequency domains. Unlike existing multi-objective optimization methods that linearly combine multiple attributes to form a composite scalar objective function, the MOEA incorporates the concept of Pareto’s domination to evolve a family of non-dominated solutions along the Pareto optimal frontier. Further, each of the objective components can have different priorities or preferences to guide the optimization from individual design specifications rather than manually pre-weighting the objective functions. Besides the flexibility of specifying a low-order controller structure to simplify the design and implementation tasks, the design approach also allows control engineers to interplay and examine different trade-offs among the multiple performance requirements. Such an evolutionary 'intelligent' CACSD methodology for optimal ULTIC designs has been successfully applied to many control engineering applications[2-4].

The overall architecture of the evolutionary CACSD methodology for optimal ULTIC systems is presented in Section 2, which includes the ULTIC system formulation and formation of various design specifications commonly adopted in practical applications. Validation of the methodology against practical ULTIC design problem for a single-input single-output (SISO) non-minimal phase plant is given in Section 3. Conclusions are drawn in Section 4.

2. Performance Based Design Unification and Automation

Almost all types of LTI controllers are in the form of a transfer function matrix or its bijective state-space equation when the design is eventually complete. The order and the coefficients of the transfer function, however, vary with the control law or a compromise design objective as to satisfy certain design specifications. For example, a controller designed from the linear quadratic regulator (LQR) scheme tends to offer a minimized quadratic error with some minimal control effort, while an H_∞ controller provides the robust performance with a minimal value of mixed sensitivity function. Although the obtained coefficients or orders of these two types of controllers may be different, the common purpose of both control laws is to devise an LTI controller that could guarantee a closed-loop performance to meet certain customer specifications in either the time or the frequency domain.

Therefore a step towards the unification of LTI control laws is to coin the controller design by meeting practical performance specifications via CACSD optimization approach, instead of by a particular control scheme or in a confined problem domain. This CACSD unified approach should eliminate the need of pre-selecting a specific control scheme for a given application, so as to form a performance-prioritized unified design that is easily understood and applicable to practical control engineers. Further, it should be capable of incorporating performance specifications in both the time and frequency domains that engineers are familiar with, and take into account various system constraints[12-14].

2.1. *The Overall Design Architecture*

The overall evolutionary CACSD paradigm for ULTIC systems is illustrated in Fig. 1. As highlighted in the Introduction, design unification of LTI control system can be formulated as an interactive multi-objective optimization problem that searches for a set of Pareto optimal controllers satisfying the often-conflicting practical performance requirements. Such a design optimization cycle accommodates three different modules: the interactive human decision-making module (control engineer), the optimization module (MOEA toolbox[15]) and the control module (system and specifications). According to the system performance requirements as well as any *a-priori* knowledge on the problem on-hand, control engineers may specify or select a set of desired specifications from a template[15] and forms a multiple-cost function in the control module, which need not necessarily be convex or confined to a particular control scheme. These ULTIC design specifications can also incorporate different performances in both the time and frequency domain or other system characteristics such as poles, zeros or etc., as desired. Based on these performance specifications, responses of the control system consists of the set of input/output signals, the plant model and the candidate controller that is recommended from the optimization module are evaluated so as to determine the different cost values for each design specification in the multiple-cost function.

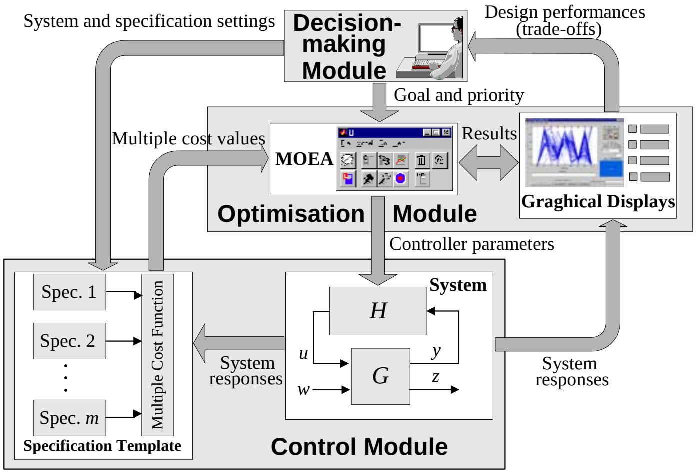


Fig. 1. A general CACSD architecture for evolutionary ULTIC systems

According to the evaluation result of the cost function in the control module and the design guidance, if any, such as goal and priority information from the decision-making module, the optimization module (MOEA toolbox[15]) automates the ULTIC design process and intelligently searches for the 'optimal' controller parameters that best satisfy the set of performance specifications. On-line optimization progress and simulation results, such as the design trade-offs or convergence trace can be displayed graphically and feedback to the decision-making module. In this way, the overall ULTIC design environment can be supervised and monitored effectively, which helps control engineers in making any further actions such as examining the competing design trade-offs, altering the design specifications, adjusting goal settings that are too stringent or generous, or even modifying the control and system structure if necessary. This man-machine interactive design and optimization process maybe proceeded until all design specifications have been met or the control engineer is satisfied with the control performances. One merit of such approach is that the design problem as well as interaction with the optimization process is closely linked to the environment of that particular application. A control engineer, in most cases, is not required to deal with any details that are related to the optimization algorithm or to worry about any possible ill-conditioning problem in the designs[1].

2.2. *Control System Formulation*

A general control system configuration for posing performance specifications is shown in the control module of Fig. 1. The operator G is a 2×2 block transfer matrix mapping the inputs w and u to the outputs z and y[12]:

$$\begin{bmatrix} z \\ y \end{bmatrix} = \begin{bmatrix} G_{11} & G_{12} \\ G_{21} & G_{22} \end{bmatrix} \begin{bmatrix} w \\ u \end{bmatrix} \tag{1}$$

The actual process or plant is represented by the sub-matrix G_{22}, i.e., the nominal model G_0, which is linear time-invariant and may be unspecified except for the constraint of lying within a given set Π ('uncertainty modeling'). H is the ULTIC controller to be designed in order to satisfy all specifications and constraints in the system as given by

$$H_{i,j}(s) = \frac{p_{i,j,n}s^{n-m-1} + \cdots + p_{i,j,m+2}s + p_{i,j,m+1}}{p_{i,j,m}s^{m} + \cdots + p_{i,j,1}s + p_{i,j,0}} \tag{2}$$

where i, j denotes the respective elements in the transfer matrix and $p_{i,j,k} \in \Re^{+}\ \forall\ k \in \{0, 1, ..., n\}$ are the coefficients to be determined in the design; y is the signal that the controller has access to, and u is the output of the controller with usually a hard constraint saturation range such as the limited drive voltage or current. The mapping from the exogenous inputs w (disturbances, noise, reference commands etc.,) to the regulated outputs z (tracking errors, control inputs, measured outputs etc.,) contains all the input-output maps of interest[12]. As illustrated in Fig. 1, the evolutionary CACSD for ULTIC systems is to find an optimal controller H that minimizes a set of performance requirements in terms of magnitude or norm of the map from w to z in both the time and frequency domains, subject to certain constraints on the behavior of the system.

2.3. ***Performance Specifications***

In developing the ULTIC systems, a set of objectives or specifications is often formed as to reflect the various performance requirements that are needed in designing a practical control system. Existing CACSD approaches require the performance index for these design objectives to be within a convex set or restricted to a confined problem domain, which may be impractical. In contrast, there is no hard limitation or objectives transformation needed in the evolutionary ULTIC system designs. This advantage allows many system constraints or conflicting specifications in both the time and frequency domains to be easily incorporated in the design, which are unmatched using conventional CACSD methods. To guide the *a-posteriori* non-deterministic evolution towards the global optimum, the evolutionary approach merely requires a performance index to indicate the relative strength for each candidate design, which is naturally available or can be easily formulated for most practical control applications. In order to address the various design specifications commonly accommodated in practical control applications, it is essential that the design objectives formulated in ULITC systems should at least reflect the following performance requirements:

A. Stability

Stability is often the first concern in any control system designs, which could be determined by solving the roots of the characteristic polynomials. The cost of stability can then be defined as the total number of unstable closed-loop poles or the positive poles on the right-hand-side of the s-plane as given by Nr{Re(eig) > 0}, i.e., no right-hand poles on the s-plane indicates that the system is stable and vice versa.

B. Step Response Specifications

Practical control engineers often address system transient and steady-state performances in terms of time domain specifications. These time domain performances are specified upon step response since it gives a good indication of the response for the controlled variable to command inputs that are constant for long periods and occasionally change quickly to a new value. For a SISO system, the performance requirement of steady-state accuracy can be defined as $e_{ss} < 1 - y(t)_{t \to \infty}$, i.e., the difference between the actual response of the commanded variables after the system is settled down.

C. Disturbance Rejection

The disturbance rejection problem is defined as follows: find a feedback controller that minimizes the maximum amplitude (H_∞ norm) of the regulated output over all possible disturbances of bounded magnitude. A general structure to represent the disturbance rejection for a broad class of control problems is given in Fig. 2, which depicts the particular case where the disturbance enters the system at the plant output. The mathematical representation is given by,

$$\begin{aligned} y &= z = G_0 u + W_1 d \\ \frac{y}{d} &= W_1 \left(I + G_0 H \right)^{-1} = W_1 S \end{aligned} \tag{3}$$

The matrix S is known as the *sensitivity function* and the maximum singular values of S determines the disturbance attenuation, since S is in fact the closed-loop transfer function from disturbance d to the measured output y. W_1 is the desired disturbance attenuation factor, which is often a function of frequency to allow a different attenuation factor at each frequency. The disturbance attenuation specification may thus be given as

$$\bar{\sigma}(S) < \left\| W_1^{-1} \right\|_\infty \Rightarrow \left\| W_1 S \right\|_\infty < 1 \tag{4}$$

where $\bar{\sigma}$ defines the largest singular value of a matrix.

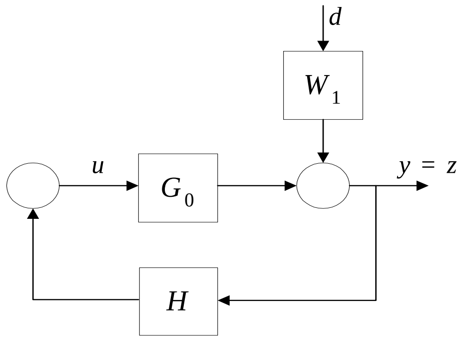


Fig. 2. A disturbance rejection problem

D. Robust Stability

It is important that the designed closed-loop system is stable and provides guaranteed bounds on the performance deterioration, even for 'large' plant variations that maybe occurred in practical applications. Roughly speaking, a robust stability specification requires some design specifications to be hold, even if the plant G_0 is replaced by any G_{pert} from the specified set Π of possible perturbed plants.

Small Gain Theorem: Suppose the nominal plant G_0 in Fig. 3 is stable with the multiplicative uncertainty Δ being zero. Then the size of the smallest stable Δ for which the system becomes unstable is[16]

$$\bar{\sigma}(\Delta) = \frac{1}{\bar{\sigma}(T)} = \left\| \frac{I + G_0 H}{G_0 H} \right\|_\infty \tag{5}$$

Therefore the singular value Bode plot of the *complementary sensitivity function T* can be used to measure the stability margins of the feedback system in face of multiplicative plant uncertainties. The multiplicative stability margin is, by definition, the 'size' of the smallest stable Δ that destabilizes the system as shown in Fig. 3. According to the small gain theorem, the smaller $\bar{\sigma}(T)$ is, the greater the size of the smallest destabilizing multiplicative perturbation will be and, hence, the greater the stability margins of the system. The stability margin of a closed-loop system can thus be specified via the singular value inequalities such as

$$\overline{\sigma}(T) < \left\|W_2^{-1}\right\|_\infty \Rightarrow \left\|W_2 T\right\|_\infty < 1 \qquad (6)$$

where $\left\|W_2^{-1}\right\|_\infty$ are the respective sizes of the largest anticipated multiplicative plant uncertainties.

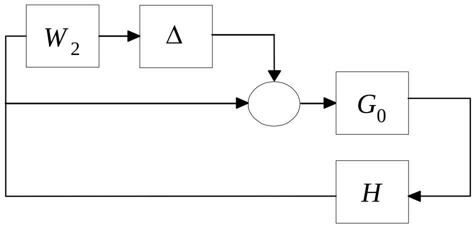


Fig. 3. Stability robustness problem with multiplicative perturbation

E. Actuator Saturation

In a practical control system, the size of actuator signals should be limited since a large actuator signal may be associated with excessive power consumption or resource usage, apart from its drawback as a disturbance to other parts of the systems if not subject to hardware limitation. A general structure for saturation nonlinearities at the input of the plant is shown in Fig. 4. To pose this problem, a saturation function is defined,

$$\mathrm{Sat}(u) = \begin{cases} u & |u| \le U_{\max} \\ U_{\max}\,\mathrm{sgn}(u) & |u| \ge U_{\max} \end{cases} \qquad (7)$$

Let the plant be described as $G_0u = G_0 \cdot \mathrm{Sat}(u)$, the objective is to design an optimal ULTIC controller H that satisfies all the design specifications with an allowable control effort of $\max(u) \le U_{\max}$, so as to stay in the linear region of the operation. Note that performances of the closed-loop system such as tracking accuracy and disturbance attenuation are bounded by the actuator saturation specification, i.e., a smaller control effort often results in a poorer performance in tracking and disturbance rejection due to the limited control gain in order to operate the system in a linear region. In addition, the stability for such a system will mean the local stability of the nonlinear system.

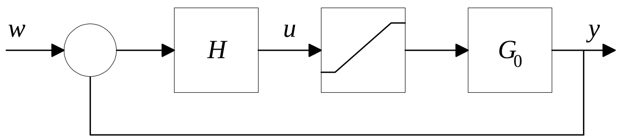


Fig. 4. Saturation nonlinearities at the plant input

F. Minimal Controller Order

It is often desired that the controller to be designed in practical control system is as simple as possible, since a simple controller would require less computation and implementation effort than a higher-order controller[17]. It is thus useful to include the order of ULTIC controller as one of the design specification here, in order to find the smallest-order controller that satisfies all the performance requirements and system constraints.

The performance and robustness specifications that are formulated above cover the usual design requirements in many practical control applications. Note that other design specifications such as phase/gain margin, time delay, noise rejection etc., could also be easily added to the ULTIC system in a similar way, if desired. As addressed in the Introduction, designing an optimal ULTIC system requires simultaneously optimizing multiple controller coefficients to satisfy the set of conflicting design specifications. It leads to a multi-dimensional and multi-modal design problem characterized by the multi-objective performance indices, which can be tackled via a multiobjective evolutionary algorithm.

3. An Evolutionary ULTIC Design Application

In this section, the control system design application of a non-minimum phase SISO plant using an MOEA toolbox[15] is presented to illustrate the effectiveness of the evolutionary ULTIC design methodology. Considering the following non-minimal phase plant as studied in[18]:

$$G_0(s) = \frac{-1.3(s-5.5307)(s+4.9083)}{s(s+0.3565-5.27j)(s+0.3565+5.27j)(s+0.0007)} \qquad (8)$$

This nominal model has a 'non-minimum phase' zero at z = 5.5307 and a nearly unstable pole at $p = -0.0007$, which makes it an interesting robust control design problem. Here, the aim is to design an ULTIC controller that meets a set of time and frequency domain performance requirements, while satisfying certain system constraints such as actuator saturation. Fig. 5 shows the overall design block diagram of the ULTIC system, which includes eight design objectives and one hard actuator constraint to be satisfied as listed in Table 1. The underlying aim of setting the priority vector in the second last column of Table 1 is to obtain a controller that first stabilizes the system within the actuator saturation limit for hardware implementation. Note that the actuator saturation is set as a hard constraint reflecting the hard limit of this performance requirement, which requires no further minimization if the control action *u* is within the saturation limit. Further, the system must be robust to plant uncertainty and disturbance attenuation under the level of tolerances as defined by the weighting functions of W_1 and W_2 in Fig. 6 [18]. Having fulfilled these requirements, the system should also satisfy some time domain specifications as defined by the transient and steady-state responses. Although determination of the objective and the priority settings may be a subjective matter and depends on the performance requirements, ranking the priorities may be unnecessary and can be ignored for a ‘minimum-commitment’ design[19]. If, however, an engineer commits himself to prioritizing the objectives, it is a much easier task than weighting the different objectives that are compulsory in objective function aggregation approaches[6].

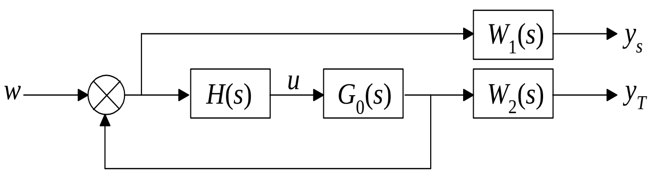


Fig. 5. Block diagram of the ULTIC system design

Table 1. Time and frequency domain design specifications for the non-minimal phase plant

Design specification		Objective	Goal	Priority	Constraint
Freq.	1. Stability (closed-loop poles)	*Nr*[Re(*eig*)] > 0} (*Sta*)	0	1	soft

	2. Disturbance rejection	S	1	3	soft
	3. Plant uncertainty	T	1	3	soft
	4. Controller order	Co	3rd	5	soft
Time domain	5. Actuator saturation	Act	0.5 V	2	hard
	6. Rise time	T_r	4 s	4	soft
	7. Overshoots	M_p	0.05	4	soft
	8. 5% settling time	T_s	7 s	4	soft
	9. Steady-state error	e_{ss}	0.01 s	4	soft

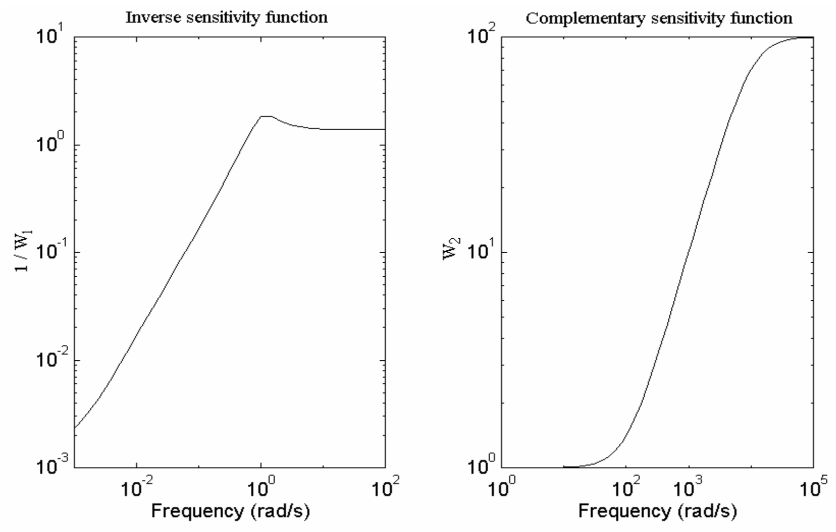


Fig. 6. Frequency responses of W_1 and W_2

The order of all candidate controllers is not fixed, while allowing its maximum to be of third-order. Parameter settings of the MOEA toolbox[15] are shown in Fig. 7. The design took less than 2 hours on a Pentium II 350MHz processor, with a population and generation size of 100. At the end of the evolution, all ULTIC controllers recommended by the toolbox have met the nine design specifications as listed in Table 1. Among these controllers, 88 are of second-order and 12 are of third-order.

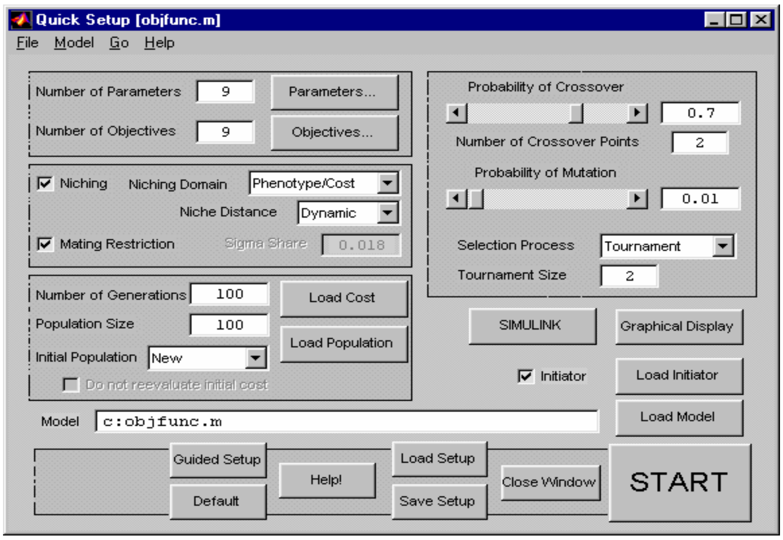


Fig. 7. Quick setups of the MOEA toolbox for the ULTIC problem

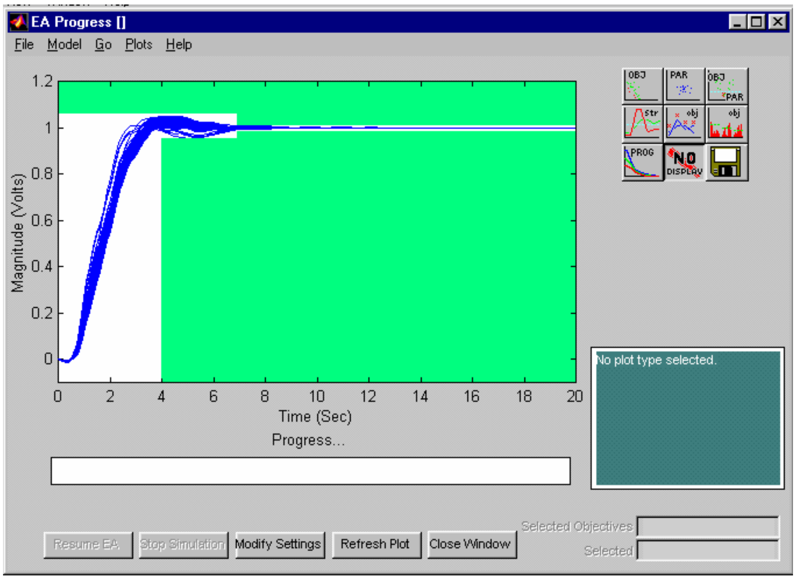
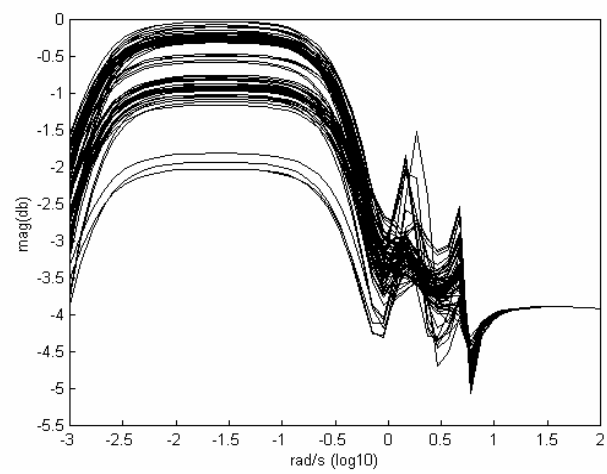
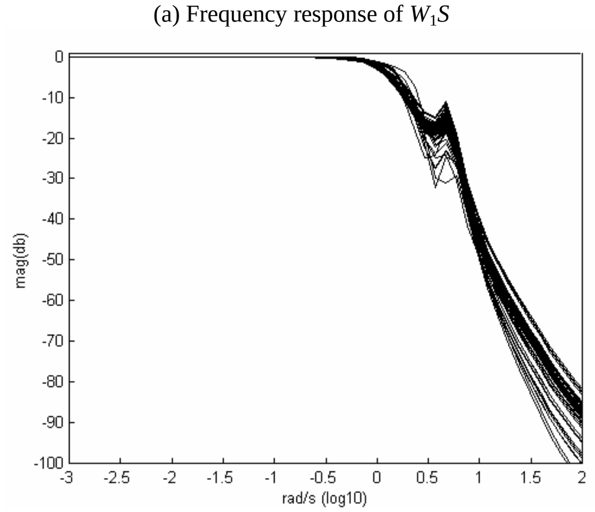


Fig. 8. The MOEA optimized output responses for the SISO system

The system closed-loop responses for these ULTIC controllers are shown in Fig. 8, where all the responses are within the clear area showing good performance of the time domain specifications. Fig. 9 shows the frequency responses of both W_1S and W_2T for all the Pareto optimal controllers, in which the gains of the responses are satisfactory less than the required magnitude of 0 dB.



(a) Frequency response of W_1S



(b) Frequency response of W_2T

Fig. 9. Frequency responses of the non-minimal phase system

To illustrate robustness of the evolutionary designed ULTIC system on disturbance rejection, a sinusoidal acted as disturbance signal was applied to the system, with an amplitude and angular frequency of 1 volt and 0.05 rad/s, respectively. The sinusoidal and its attenuated signal for all Pareto optimal ULTIC controllers are shown by the dashed and solid line in Fig. 10, respectively. Clearly, the disturbance has been attenuated successfully as required by the 2nd objective in Table 1, which had resulted a 10 times in gain reduction of the original sinusoidal signal.

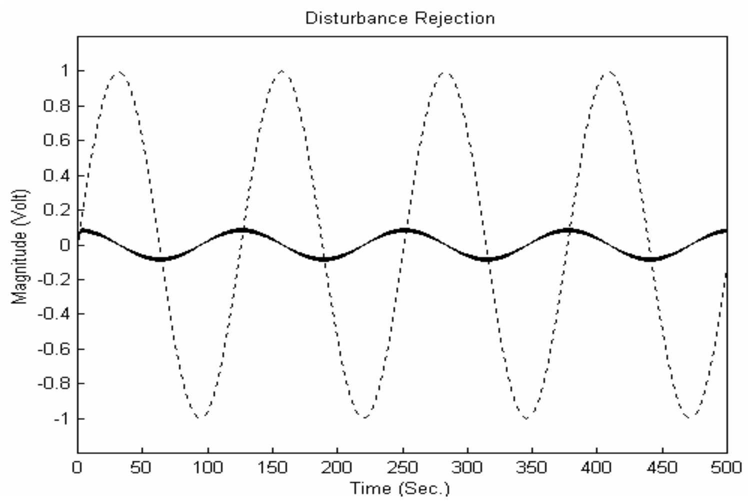


Fig. 10. The sinusoidal disturbance and its attenuated signal

Fig. 11 shows the output responses for one of the randomly chosen Pareto optimal controller with a perturbed nominal model of eqn. 8 as to study the system robustness in terms of plant uncertainties. The plant is being perturbed simultaneously upon both the zeros and poles of the nominal model in the range of

$$\frac{z_1}{4} \le z \le z_1\,, \quad \frac{p_1}{1.2} \le p \le p_1 \tag{9}$$

where $z_1 = 2z$ and $p_1 = 1.1p$; z and p is the zeros and poles of the nominal plant, respectively. It was observed that plant perturbations upon the system poles are much more sensitive than the zeros, due to the 'almost unstable' pole that is located very near to the imaginary axis, i.e., p = 0.0007. As shown in Fig. 11, the ULTIC system is able to maintain relatively good response and stability performance despite the various perturbations made upon the nominal plant.

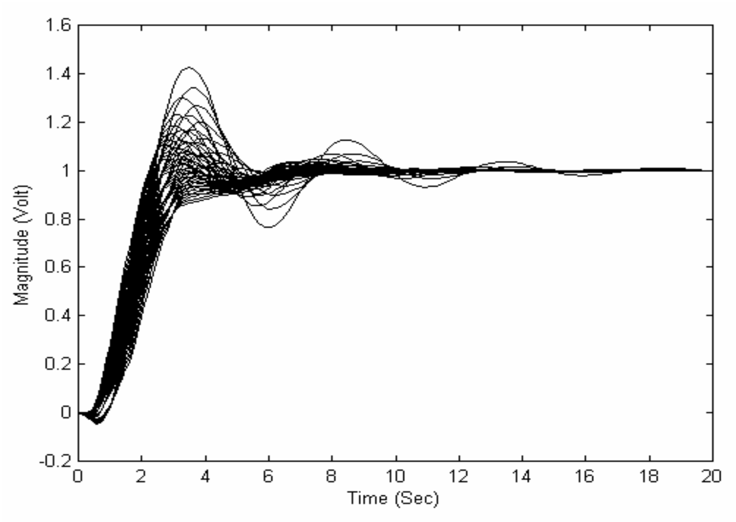


Fig. 11. Output responses of the ULITC system with plant uncertainties

Apart from the flexibility in analyzing the control performance, the evolutionary design also allows on-line examination of different trade-offs among the multiple conflicting specifications, modification of existing objectives and constraints or zooms into any region of interest before selecting one final controller for real-time implementation. The trade-off graph of the resultant 100 ULTIC controllers is shown in Fig. 12, where each line representing a solution found by the evolutionary optimization. The x-axis shows the design specifications, the y-axis shows the normalized cost for each objective and the cross-mark shows the desired goal setting for each specification. Clearly, trade-offs between adjacent specifications results in the crossing of the lines between them, whereas concurrent lines that do not cross each other indicating the specifications do not compete with one another. For example, the specification of tracking error (e_{ss}) and controller order (Co) do not directly compete against each other, whereas the sensitivity function (S) and complementary sensitivity function (T) appear to compete heavily, as expected.

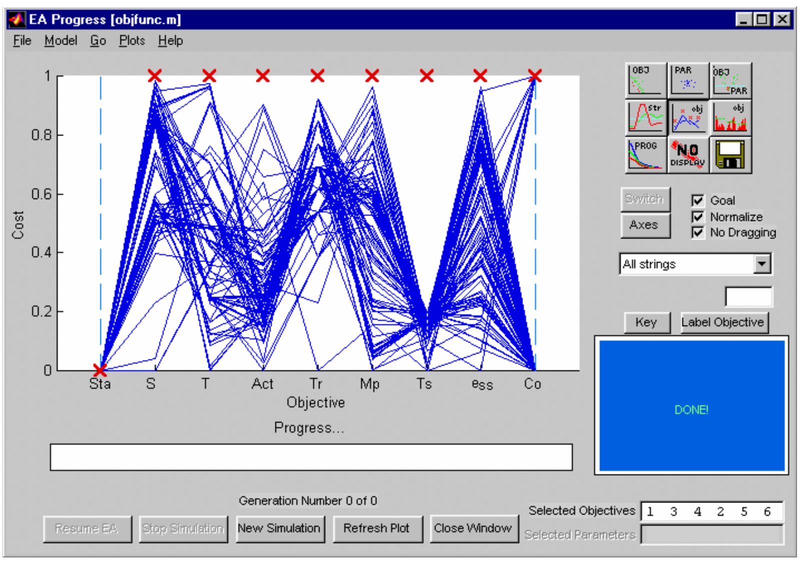
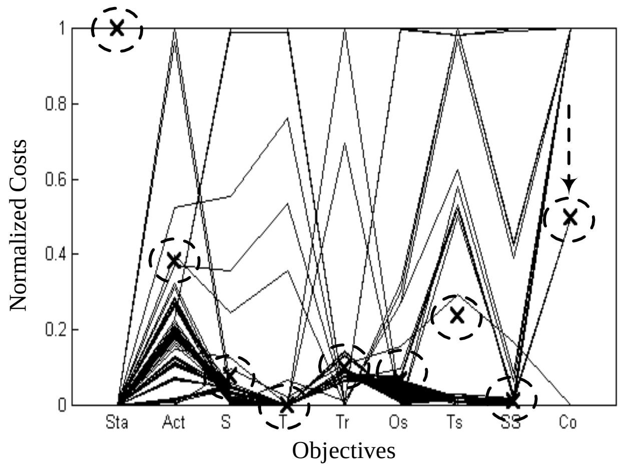
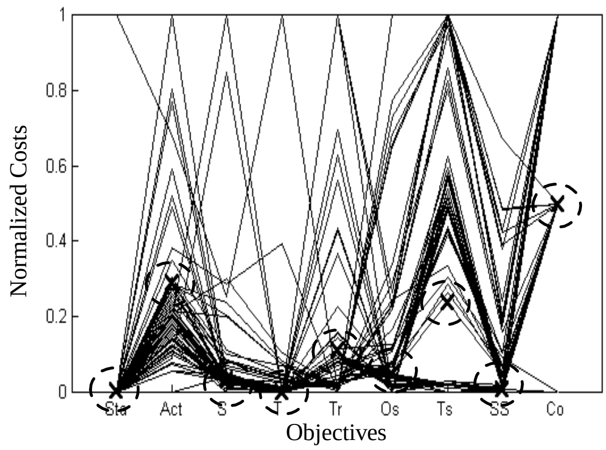


Fig. 12. Trade-off graph of the final evolutionary designed ULTIC system

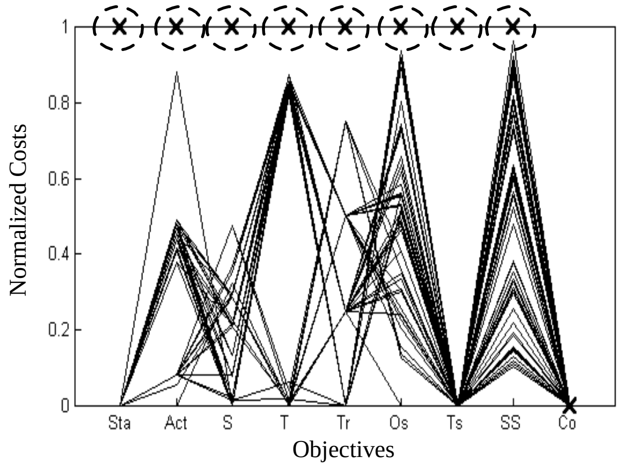
Information contained in the trade-off graph of Fig. 12 also suggests that a lower goal setting of rise time and settling time is possible, and these objectives could be further optimized to arrive at even better transient performance if desired. A powerful feature of designing ULTIC system using MOEA is that all the goal and priority settings can be conveniently examined and modified at any time during the evolution process. For example, the designer may change his preference and decide to set a goal setting of 2nd-order, instead of the 3rd-order, for the controller order specification after certain number of generations. Fig. 13 illustrates the behavior of the evolution upon online modification of this goal setting after the design in Fig. 12. Due to the sudden change of a tighter goal setting, none of the individuals manages to meet all the required specifications as shown in Fig. 13(a). After continuing the evolution for 5 generations, the trade-offs move towards satisfying the controller order specification at the performance expenses of other objectives as shown in Fig. 13(b). In Fig. 13(c), the evolution continues and again leads to the satisfaction of all the goal settings including the controller order specification, by having less room for further improvement of other design objectives or achieving less Pareto optimal solutions as compared to the one in Fig. 12. Clearly, this man-machine interactive design approach has enabled control engineers to divert the evolution into any interested trade-off regions as well as to modify certain specifications or preferences on-line, without the need of restarting the entire design cycles as required by conventional methods.



(a) Reducing the goal setting of controller order from 3rd- to 2nd- order



(b) After 5 generations



(c) After another 5 generations

Fig. 13. Effects of the evolution upon the on-line modification of goal setting

4. Conclusions

This chapter has presented an automated CACSD design methodology for uniform LTI control systems using an MOEA, which is capable of unifying different LTI design schemes under performance satisfactions and eliminating the need of pre-selecting a specific control law. Unlike conventional methods, control engineers' expertise as well as settings on goal or priority for different preference on each design specification can be easily incorporated and modified on-line according to the evolving trade-offs, without the need of repeating the whole design process. In principle, any number or combination of constraints and performance specifications can be included in the evolutionary ULTIC design if desired. Validation results upon a non-minimum phase control system illustrate the efficiency and effectives of the methodology.

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