

# Chapter XXVII

## Human–Centric Evolutionary Systems in Design and Decision–Making

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### ABSTRACT

*The chapter introduces the concept of user-centric evolutionary design and decision-support systems, and positions them in terms of interactive evolutionary computing. Current research results provide two examples that illustrate differing degrees of user interaction in terms of subjective criteria evaluation; the extraction, processing, and presentation of high-quality information; and the associated improvement of machine-based problem representation. The first example relates to the inclusion of subjective aesthetic criteria to complement quantitative evaluation in the conceptual design of bridge structures. The second relates to the succinct graphical presentation of complex relationships between variable and objective space, and the manner in which this can support a better understanding of a problem domain. This improved understanding can contribute to the iterative improvement of initial machine-based representations. Both examples complement and add to earlier research relating to interactive evolutionary design systems.*

### INTRODUCTION

Uncertainty and poor problem definition are inherent features during the early stages of

design and decision-making processes. Immediate requirements for relevant information to improve understanding can be confounded by complex design representations comprising

many interacting variable parameters. Design constraints and multiple objectives that defy complete quantitative representation and therefore require a degree of subjective user evaluation further inhibit meaningful progression. Machine-based problem representation may, initially, be based upon qualitative mental models arising from experiential knowledge, group discussion, and sparse available data. However, such representations, coupled with user intuition, play a significant role in defining initial direction for further investigation. Concepts based upon current understanding require both quantitative and qualitative exploration to generate relevant information that supports and enables meaningful progress.

The chapter presents research and development relating to powerful machine-based search and exploration systems that, through appropriate user interaction, allow both quantitative and qualitative evaluation of solutions and the extraction of information from complex, poorly understood design and decision-making domains. The integration and capture of user experiential knowledge within such systems in order to stimulate, support, and increase understanding is of particular interest. The objective is the realisation of user-centric intelligent systems that overcome initial lack of understanding and associated uncertainty, support an improving knowledge-base, allow the integration of subjective judgement, and stimulate innovation and creativity.

## **INTERACTIVE EVOLUTIONARY COMPUTATION (IEC)**

Interactive evolutionary computing (Takagi, 1996) mainly relates to partial or complete human evaluation of the fitness of solutions generated from evolutionary search. This has been introduced where quantitative evaluation is difficult if not impossible to achieve. Ex-

amples of application include graphic arts and animation (Sims, 1991), food engineering (Herdy, 1997), and hazard icon design (Carnahan, 2004). Such applications rely upon a human-centred, subjective evaluation of the fitness of a particular design, image, taste, and so forth, as opposed to an evaluation developed from some analytic model.

Partial human interaction that complements quantitative machine-based solution evaluation is also evident—for instance, the user addition of new constraints in order to generate solutions that are fully satisfactory within an evolutionary nurse scheduling system (Inoue, Furuhashi, & Fujii, 1999). Another example is the introduction of new compounds as elite solutions into selected evolving generations of a biomolecular design process (Levine, Facello, & Hallstrom, 1997).

These examples utilise a major advantage of stochastic population-based search techniques—that is, their capabilities as powerful search and exploration algorithms that provide diverse, interesting, and potentially competitive solutions to a wide range of problems. Such solutions can provide information to the user which supports a better understanding of the problem domain whilst helping to identify best direction for future investigation (Parmee & Bonham, 1999), especially when operating within poorly defined decision-making environments. Extracted information supports development of the problem representation in an iterative, interactive evolutionary environment. Interactive evolutionary design systems (IEDSs) represent a human-centric approach (Parmee, 2002; Parmee, Watson, Cvetkovic, & Bonham, 2000) that generate and succinctly present information appertaining to complex relationships between the variables, objectives, and constraints that define a developing decision space.

In an attempt to categorise these various forms of IEC, it is possible to view complete

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