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A novel interactive preferential evolutionary method for controller tuning in chemical processes☆

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ABSTRACT

In response to many multi-attribute decision-making (MADM) problems involved in chemical processes such as controller tuning, which suffer human's subjective preferential nature in human–computer interactions, a novel affective computing and preferential evolutionary solution is proposed to adapt human–computer interaction mechanism. Based on the stimulating response mechanism, an improved affective computing model is introduced to quantify decision maker's preference in selections of interactive evolutionary computing. In addition, the mathematical relationship between affective space and decision maker's preferences is constructed. Subsequently, a human–computer interactive preferential evolutionary algorithm for MADM problems is proposed, which deals with attribute weights and optimal solutions based on preferential evolution metrics. To exemplify applications of the proposed methods, some test functions and, emphatically, controller tuning issues associated with a chemical process are investigated, giving satisfactory results.

1. Introduction

Many issues in chemical process control community could be considered as multi-attribute decision-making (MADM), such as controller parameter tuning. Although numerous model-based and data-driven methods have been popularly employed to solve the problems, these researches are rarely concerned with human's subjective judgments on the decision-making.

A majority of multiple-attribute decision-making methods [1–4] concerns with choosing excellent solutions in several decision-making schemes according to attribute weights and values associated with different interval expectations. Xu and Yager [5] have proposed to divide a decision cycle into a plurality decision cycle and set the dynamic multiple attribute for more uncertainty attribute decision problems. Osman *et al.* [6] have introduced optimization algorithms to obtain attribute weights in MADM. Little attention has been paid to decision-makers' subjective preferences, which plays dominant roles in dealing with decision-making issues.

Affective computing [7–13] is a new research issue in artificial intelligence, whose relevant technologies are used in various application fields. For example, Novak *et al.* [14] conducted a survey about the work on data fusion and system adaptation using autonomic nervous system responses in psychophysiology and physiological computing. Angeliki *et al.* [15] introduced a Gaussian mixture model-based approach computing a mapping from a set of observed audio–visual cues to an underlying emotional state where emotions can be continuously tracked and dimensional emotional descriptions are given with body language and improvised dyadic interactions. Martin *et al.* [16] proposed a fully automatic audiovisual recognition approach based on long short-term memory modeling of word-level audio and video features, which was built on previous studies that long range context modeling tends to increase accuracies of emotion recognition. However, quantitative description of affective transitions affected by persistent external stimuli still presents a challenge.

Generally, attributes conflict each other and the selection of MADM solutions is not a straightforward task. To solve the decision-making problems with objectives far from complete structure and quantification, interactive evolutionary computation (IEC) [17,18] is recognized as an effective approach. As an evolutionary algorithm demanding human direct participation, IEC can help human influence the evolutions by directly evaluating individual performance. However, IEC [19,20] usually presents weakness in local searching capability and suffers human's limitations in discriminating ability with slow convergence.

Motivated by these observations, this paper proposes an affective computing based interactive preferential evolutionary algorithm to cope with MADM problems in chemical plants. Adapted to the human–computer interaction mechanism, the algorithm highlights decision-makers' preferential evolutions towards excellent solution

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options. This has been applied to both numerical examples and chemical process controller parameter tuning, leading to satisfactory results.

In this study, a model of affective computing with continuous external stimuli is proposed. The interactive preferential evolutionary mathematical description and evolutionary algorithms are introduced. The applications consist of test functions and chemical process controller tuning issues.

2. Affective Computing Models

Definition 1. A shifted external environment that human could feel and response emotionally is an affective stimulus.

An improved affective computing model, STAM, is established to compute the affective transitions driven by affective stimulus persistently, with the procedure as follows.

Step 1. According to the pioneer work [7,8], a one-dimensional affective space vector is designed as

$$\boldsymbol{\Phi}_s^n = \left\{s_1^n, s_2^n, s_3^n\right\} \tag{1}$$

where components s_i^n ($i = 1, 2, 3$) correspond to affective strengths associated with "happiness", "calmness" and "sadness", respectively, constrained by $s_1^n + s_2^n + s_3^n = 0$, and n is the number of interactions. Only the affective component with positive and the largest absolute value has effect at any time.

Step 2. The affective changing quantity driven by affective stimuli is characterized by

$$\Delta\boldsymbol{\Phi}_s^n = \boldsymbol{\Phi}_s^n \boldsymbol{p}_s \tag{2}$$

where $\boldsymbol{p}_{s(3\times 3)}$ is the affective stimulating matrix. The changes of affective space driven by affective stimuli are

$$\boldsymbol{\Phi}_s^{n+1} = \boldsymbol{\Phi}_s^n + \Delta\boldsymbol{\Phi}_s^n. \tag{3}$$

Step 3. An artificial psychological stress model $y = A\varpi^x$ [7] is described as the affective stimulus of STAM, whose output, y, changes with affective stimuli.

Step 4. ϖ is the quantitative parameter of shifted affective stimuli to measure the affective changes, with $\varpi = \partial_n - \partial_{n-1}$, where ∂_n is the affective stimulus at timescale n ($n = 1, 2, \ldots$). Therefore, we have $y = A(\partial_n - \partial_{n-1})^x$, where A and x are the adjustable parameters in response to affective stimuli.

Step 5. According to Eq. (2), the affective space expression is

$$\begin{aligned}\boldsymbol{\Phi}_s^{n+1} &= \boldsymbol{\Phi}_s^n + y\boldsymbol{\Phi}_s^n = \boldsymbol{\Phi}_s^n + AB^x\boldsymbol{\Phi}_s^n \\ &= \boldsymbol{\Phi}_s^n + A(\partial_n - \partial_{n-1})^x\boldsymbol{\Phi}_s^n.\end{aligned} \tag{4}$$

The affective components correspond to

$$\boldsymbol{s}_i^{n+1} = \boldsymbol{s}_i^n + AB^x\boldsymbol{s}_i^n = \boldsymbol{s}_i^n + A(\partial_n - \partial_{n-1})^x \cdot \boldsymbol{s}_i^n.$$

Three fundamental properties of STAM have been proved: (a) only one component of the affective space corresponds to the terminal state of affective transitions; (b) components of the affective space should take values in the range $[-1, 1]$, *i.e.*, $s_k^n \in [-1, 1]$; (c) in MADM, changes of attributes may create affective stimuli. With $S_1(x) \in [a, b]$ [Eq. (1)] and $\mu(x) \in [0, 1]$ specified as the strengths of "happiness" and affective preferential membership degrees, respectively, the linear mapping $\frac{S_1(x)-a}{b-a} = \mu(x)$ can be used to convert the affective space into affective preferential membership values.

3. Interactive Preferential Evolutionary Algorithms

Definition 2. In the context of attribute weights and values associated with multi-attribute decision-making, human's affective satisfaction degree of external attributes is a two-dimensional affective preference, expressed as

$$\textbf{preference} = \{v_i, \omega_i\}$$

where, v_i is the expected optimum solution of each attribute, ω_i is the weight coefficient of each attribute, and i is the number of attributes.

3.1. Mathematical descriptions

Since most of practical MADM problems usually suffer inexplicit objective functions, human's subjectivity significantly affects decision-making. It is reported that with professional knowledge and experiences, human's affective preferences towards decision-making could be rather scientific, which helps solve decision-making problems easily and quickly. Inspired by this idea, we establish a preferential interactive evolution formulation in terms of constrained nonlinear programming

$$\begin{aligned}&\text{opt} \quad \textbf{preference}\left(m_j\right) \\ &\text{s.t. MADM's} \quad \text{desired} \;\; \text{best} \quad \text{solutions} \\ &\qquad\qquad\quad \sum \omega_i = 1\end{aligned}$$

where m_j is the objective functions of the decision-making problem, j is the number of decision vector, and i is the number of attributes.

3.2. An improved multi-attribute decision-making method

Based on the MADM method with partial attribute weight information and exact real attribute values [21], we change the original satisfaction index to a relative satisfaction index, which is the decision-making basis of each generation's solutions. Meanwhile, a global satisfaction index is defined to show affective interactive evolutions in the decision-making implementation.

To obtain the evolutionary decision-making attribute weight, we choose the most excellent solution from the existing decision solutions. An improved multi-attribute decision-making procedure is as follows.

(1) The decision-making matrix is partitioned to the form of

$$\tilde{\boldsymbol{A}} = \left(\tilde{a}_{ij}\right)_{n\times m} \tag{5}$$

(2) The standard matrix is specified as

$$\tilde{\boldsymbol{R}} = \left(\tilde{r}_{ij}\right)_{n\times m} \tag{6}$$

(3) The single objective optimization model is constructed as

$$\begin{cases}\max z_i(\omega) = \sum\limits_{j=1}^{m} r_{ij}\omega_j, \quad i \in N \\ \qquad\qquad \text{s.t.} \quad \omega \in \Phi\end{cases} \tag{7}$$

where, N is the number of attributes, $\omega = (\omega_1, \omega_2, \ldots, \omega_m)$ signifies the most excellent solution, and $z_i^{\max} = \sum\limits_{j=1}^{m} r_{ij}\omega_j$ is the ideal value of comprehensive positive attribute of the scheme $x_i (i \in N)$.