

Approaches to Affective Computing and Learning towards Interactive Decision Making in Process Control Engineering

SU Chong¹ LI Hong-Guang¹

Abstract Numerous multi-objective decision-making problems related to industrial process control engineering such as control and operation performance evaluation are being resolved through human-computer interactions. With regard to the problems that traditional interactive evolutionary computing approaches suffer i.e., limited searching ability and human's strong subjectivity in multi-objective-attribute decision-making, a novel affective computing and learning solution adapted to human-computer interaction mechanism is explicitly proposed. Therein, a kind of stimulating response based affective computing model (STAM) is constructed, along with quantitative relations between affective space and human's subjective preferences. Thereafter, affective learning strategies based on genetic algorithms are introduced which are responsible for gradually grasping essentials in human's subjective judgments in decision-making, reducing human's subjective fatigue as well as making the decisions more objective and scientific. Affective learning algorithm's complexity and convergence analysis are shown in Appendices A and B. To exemplify applications of the proposed methods, ad-hoc test functions and PID parameter tuning are suggested as case studies, giving rise to satisfying results and showing validity of the contributions.

Key words Affective computing, affective learning, interactive evolutionary computing (IEC), decision-making, process control

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It is acknowledged that distributed control systems (DCS) have played increasingly important roles in process control engineering nowadays. However, a variety of optimization and decision-making related tasks, such as controller tuning and operation performance assessment, still rely mainly on human operators' experiences and understanding of the processes, and thus suffering strong subjectivity.

Interactive evolutionary computation (IEC)^[1–2] has been recognized as an effective approach to accommodate complex decision-making relevance, where the objectives involved are usually far from completely structured and quantified, or implicitly expressed due to the uncertainty associated with decision makers' preferences. As a kind of evolutionary algorithms demanding human direct participation, its prominent features lie in the fact that human may influence the evolutions by directly evaluating individual performances. For example, Lai et al.^[3] put forward a method to solve image segmentation problems using interactive evolutionary computation under genetic algorithms framework. John et al.^[4] introduced hierarchical concepts into interactive evolutionary computing, separating global and local searching thereby solving regional nonlinear optimization problems involved in video working environments. Nonetheless, IEC suffers human's limitations in discriminating abilities that account for slow convergence, even if the individuals are in the vicinity of the optimum solutions. In other terms, IEC usually reveals weakness in local searching capability as well as in overcoming human's subjective deviation for quantitatively evaluating excellent solutions.

Human-computer interactive models concerning human behaviors, languages, facial expressions, etc. can be classified into three categories^[5–6]: 1) artificial action cycle models that describe mental behaviors through human-computer interactions; 2) GOMS (goals, operators, methods, and selection rules) models^[7–8] that stress on semantic representations of goals, operators, methods and selection

rules but respond to cognitive actions slowly; 3) artificial process models including consciousness, driving, cognitive systems that are commonly used in comprehensive analysis such as reasoning and problem solving. However, the existing human-computer interactive models remain theoretical rather than applicable in scope.

Alternatively, affective computing becomes a new emerging research issue that targets the emotion of computer agents to improve their autonomy, adaptability, and social interactive ability. Currently, majority of related researches are concerned with theoretical relevance and simulation issues. Specifically, hidden Markov models (HMM)^[9] have been adapted to represent human's spontaneous transitions with certain external stimuli added. Therein, adjustable parameters could be modified to manage the speed and amplitude associated with transitions. Additionally, approaches to assign affective matrix are available for personality based OCC (Ortony, Clore, Collins) models^[10], which could effectively express human's affective changes when externally stimulated. Besides, conceptual affective entropy, energy, strength and threshold were provided by some researchers^[11] as well. Whereas, it turns out that the above-cited models are confined by specific models in terms of applications. For instance, hidden Markov chain models are adapted to the spontaneous transitions driven by singular external stimulus only, which inevitably discourages the applications in human-computer interactive environments. It is conceivable that the problem of how to quantitatively describe affective transitions impacted by persistent external stimuli still presents a challenge.

In contrast to the achievement of affective computing, relatively few attentions have been paid to affective learning ever since. In the descriptions of virtual affective models, Van Kesteren et al.^[12] addressed affective learning problems but rarely covered them in detail. Ishihara et al.^[13] employed affective algorithms to deal with traffic signal systems. Owing to simple affective models employed, they only described affective responses to a certain external stimulus, rarely taking into account of shifted external stimuli.

Rudolph et al.^[14] presented four abstract evolutionary algorithms for multi-objective optimization and theoretical

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results that characterize their convergence behavior. Based on these results which offered the desired limit behavior or not, convergence properties are given. Ishibuchi et al.^[15] extend a multi-objective genetic algorithm (MOGA) in their former studies to a multi-objective genetic local search (MOGLS) algorithm where a local search procedure adjusts the selection (i.e., inclusion or exclusion) of each candidate rule. Furthermore, a learning algorithm of rule weights (i.e., certainty factors) is combined with their MOGLS algorithm. Gacto et al.^[16] proposed specific multi-objective evolutionary algorithm to obtain more compact fuzzy logic controllers as a way of finding the best combination of rules, with improving the system performance to better solve the control problem of heating, ventilating, and air conditioning (HVAC) system. Fazzolari et al.^[17] presents an overview of multi-objective evolutionary fuzzy systems, describing the main contributions in this field and providing a two-level taxonomy of the existing proposals, in order to outline a well established framework that could help researchers working on significant further developments. Seah et al.^[18] defined an “expensive” objective to obtain the Pareto-optimal solution set under a limited resource budget towards multiple criteria assessments in predicting the Pareto front rank of the offspring in multi-objective evolutionary algorithms (MOEAs). But clear objective functions always must be need.

Motivated by getting rid of human’s participation in IEC thereby reducing the impacts of subjective judgments on decision-making, this paper proposes an approach to affective computing adapted to human-computer interactive mechanism. Successively, a kind of interactive affective learning models is presented, along with enabling algorithms, aiming at grasping essentials in human’s affective preferences towards multi-objective decision-making. The algorithm’s time complexity and space complexity analyses are provided, along with proving the algorithm’s convergence. The proposed methodologies are applied to both numerical examples and parameter tuning of PID controllers, leading to satisfactory results.

The remainder of this paper is organized as follows. Section 1 presents a method of affective computing with continuous external stimuli. This is followed in Section 2 by an in-depth investigation on interactive affective learning philosophies as well as enabling algorithms. In Section 3, multi-objective-attribute evaluation approaches subject to human’s preferences are introduced. Section 4 provides case studies consisting of test functions and PID controller tuning. Section 5 concludes the article and assesses the future perspectives. Affective learning algorithm’s complexity and convergence analyses are shown in Appendices A and B.

1 Affective computing models

Definition 1 (Affective stimulus). A shifted external environment which human could feel and respond emotionally refers to an affective stimulus.

In order to quantitatively compute the affective transitions driven by affective stimulus persistently, an improved affective computing model, STAM (stimulated transferring affect model), is suggested as follows.

Step 1. According to [9–11], specify an affective space as

$$\Phi_s^n = \{s_1^n, s_2^n, s_3^n\} \quad (1)$$

where the components, s_i^n ($i = 1, 2, 3$), represent the affective strengths associated with “happiness”, “calmness”, and “sadness”, respectively, constrained by ($s_1^n + s_2^n + s_3^n = 0$) similar to that of HMM. It is noted that, at any time, only the affective component with positive and largest absolute value takes effect.

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

$$\Delta\Phi_s^n = \Phi_s^n p_s \quad (2)$$

where $p_s(3 \times 3)$ denotes the affective stimulating matrix. Thus, the changes of affective space driven by affective stimuli are described as:

$$\Phi_s^{n+1} = \Phi_s^n + \Delta\Phi_s^n \quad (3)$$

Step 3. Consider an artificial psychological stress model $y = A\varpi^x$ ^[9] as the affective stimulus description of STAM, whose output, y , changes with affective stimuli.

Step 4. In order to measure the affective changes, ϖ is suggested as the standard quantitative parameter of shifted affective stimuli, i.e., $\varpi = \partial_n - \partial_{n-1}$, where ∂_n corresponds to the affective stimulus at timescale n ($n = 1, 2, \dots$). Therefore, we have $y = A(\partial_n - \partial_{n-1})^x$.

Step 5. According to (3), we get the affective space expression as follows:

$$\begin{aligned} \Phi_s^{n+1} &= \Phi_s^n + y\Phi_s^n = \Phi_s^n + A\varpi^x\Phi_s^n = \\ &\Phi_s^n + A(\partial_n - \partial_{n-1})^x\Phi_s^n \end{aligned} \quad (4)$$

The affective components correspond to

$$s_i^{n+1} = s_i^n + A\varpi^x s_i^n = s_i^n + A(\partial_n - \partial_{n-1})^x \cdot s_i^n \quad (5)$$

where A and x are used as adjustable parameters responsible for human’s different personalities in response to affective stimuli.

In what follows, we present two fundamental properties associated with STAM.

Property 1 (Uniqueness). Only one component of the affective space accounts for the terminal state of affective transitions driven by a certain affective stimulus.

Property 2 (Boundedness). Components of the affective space should take values in the range $[-1, 1]$, i.e., $s_k^n \in [-1, 1]$.

Theorem 1. Regarding the components of STAM affective space,

$$\text{If } \sum_{n=a}^b \delta_n = 0, \text{ then } s_k^a = s_k^b \quad (b \geq a)$$

where δ_n stands for the changes of affective stimuli at timescale n , a and b stand for different timescales, A and x signify affective parameters.

Proof. According to (5) and $\delta_n = \partial_n - \partial_{n-1}$, we obtain $s_k^{n+1} = s_k^n + A\varpi_n^x s_k^n = s_k^n + A(\partial_n - \partial_{n-1})^x \cdot s_k^n$, and

$$s_k^{n+1} = s_k^0 \prod_{n=0}^n (1 + A\delta_n^x), \quad k = 1, 2, 3 \quad (6)$$

So, we have

$$s_k^{a+1} = s_k^0 \prod_{n=0}^a (1 + A\delta_n^x) \quad \text{and} \quad s_k^{b+1} = s_k^0 \prod_{n=0}^b (1 + A\delta_n^x)$$

When there is $\sum_{n=a}^b \delta_n = 0$, we have $\partial_a = \partial_b$. According to the uniqueness property, we attain $s_k^a = s_k^b$. \square

2 Affective learning algorithms

Affective learning is aiming at gradually imitating human’s affective preferences in decision-making by means of adjusting parameters of corresponding affective computing models. Consequently, during the period of human-computer interactive decision-making, computer could gradually replace the human’s subjective participation,

lessen human's subjective fatigue and promote more scientific implementations.

Definition 2 (Affective preference). Human's affective satisfaction degrees for achieved objectives in decision-making refer to affective preferences.

Property 3. In multi-objective-attribute decision-making, changes of objective-attributes may create affective stimuli, leading to a shifted affective space, where the strengths of "happiness" in the terminal response could be mapped into affective preferential membership degrees.

In the presence of that $S_1(x) \in [a, b]$ and $\mu(x) \in [0, 1]$ are specified as the strengths of "happiness" and affective preferential membership degrees with respect to objective-attribute x , respectively, the linear mapping $\frac{S_1(x)-a}{b-a} = \mu(x)$ could be employed to convert affective space into affective preferential membership.

In this sense, affective learning problems can be formulated as a constrained nonlinear programming, described as follows.

$$\begin{aligned} \min \sum_{i=1}^n [\mu(x_i) - \mu'(x_i)]^2, \quad i = 1, \dots, n \\ \text{s.t.} \quad |S_{\text{happy}}^n| \leq 1 \end{aligned} \quad (7)$$

where, for objective-attribute x_i , $\mu(x_i)$ corresponds to the mapping relationship from strength of "happiness" into membership degrees of affective preferences, $\mu'(x_i)$ corresponds to the desired preferential membership functions. Genetic algorithms can be invoked to solve this optimization problem, whose implementing steps are shown in Fig. 1, where details of multi-objective fitness index computing will be presented in Section 3.

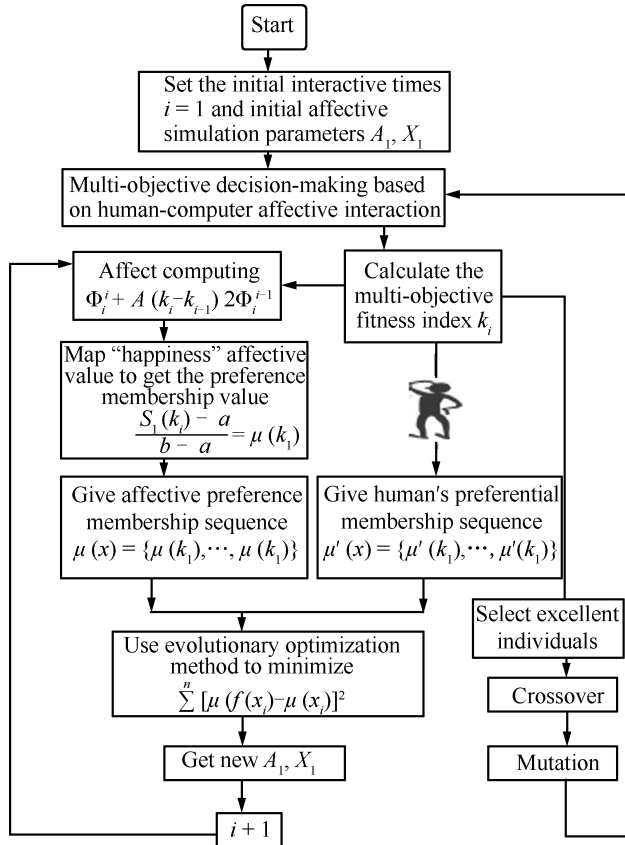


Fig. 1 Affective learning algorithm

3 Affective learning based decision-making approaches

To implement interactive multi-objective-attribute decision-making, an objective-attribute fitness assessment method is demanded, which could help human operators evaluate each generation in evolutions subject to their affective preferences.

Initially, the relative importance of an objective-attribute needs to be particularly considered. We postulate that a set of objective-attributes is expressed as

$$\text{Property-Set} = \{p_1, p_2, \dots, p_n\}, \quad i = 1, 2, \dots, n \quad (8)$$

where p_i ($i = 1, 2, \dots, n$) signify the values of objective-attributes, n is the number of the objective-attributes.

Definition 3 (Objective achievement index). Specify an objective achievement index as:

$$k = \sum_{i=1}^n \lambda_i \varphi_i \quad (9)$$

where λ_i is defined as the relative importance degrees of attribute p_i which are constrained by $\sum_{i=1}^n \lambda_i = 1$. Obviously, $k \leq 1$ implies that the objective is perfectly achieved.

Definition 4 (Fitness of attribute). A parameter φ_i is introduced to measure the fitness of attribute p_i , which is defined as

$$\varphi_i = \frac{p'_i}{\hat{p}_i} \times 100\% \quad (10)$$

where p'_i and \hat{p}_i are the actual and admissible values of p_i at the current time period, respectively.

Algorithm 1 (Relative importance). According to fuzzy analytic hierarchy process (AHP), the relative importance of each objective-attribute can be identified as follows:

Step 1. Establish priority relation matrix $F = (f_{ij})_{n \times n}$, where

$$f_{ij} = \begin{cases} 0.5, & s(i) = s(j) \\ 1.0, & s(i) > s(j) \\ 0.0, & s(i) < s(j) \end{cases} \quad (11)$$

$s(i)$ and $s(j)$ indicate the importance degrees of f_i and f_j ($i, j = 1, 2, \dots, n$), respectively.

Step 2. Transform the priority relation matrix F as follows:

$$r_i = \sum_{k=1}^n f_{ik}, \quad k = 1, 2, \dots, n, \quad r_{ij} = \frac{r_i - r_j}{2n} + 0.5 \quad (12)$$

where $R = (r_{ij})_{n \times n}$ refer to fuzzy consistent matrix.

Step 3. Compute importance degrees as follows:

$$l_i = \sum_{j=1}^n r_{ij} - 0.5, \quad i = 1, 2, \dots, n \quad (13)$$

To normalize l_i , we eventually obtain the importance degrees as

$$\lambda_i = \frac{2l_i}{n(n-1)}, \quad i = 1, 2, \dots, n \quad (14)$$

Inspired by these contributions, we introduce affective learning based interactive decision-making algorithms. Firstly, average objective fitness index of current generation K is provided to both human operators for evaluating performance and affective computing algorithms for generating affective space. Subsequently, population evolutions launch through selection, crossover and mutation operations. Meanwhile, the parameters of affective computing models are optimized in terms of imitating human's affective preferences in high fidelity. As a consequence,

with the affective learning algorithms in Section 2, computers could gradually grasp essentials in human's subjective judgments for a specific multi-objective-attribute decision-making problem, effectively lessen human's subjective fatigue, as well as promote a scientific interactive decision-making.

Algorithm 2 (Affective learning based decision-making).

Step 1. Initiate $t = 0$ and create initial population $\bar{x}_l(t)$ randomly over the global searching space.

Step 2. Specify an importance degree for each objective-attribute, and, in regard to every individual, calculate corresponding objective fitness index K based on Algorithm 1.

Step 3. Aided by computers, human operators evaluate the excellent individuals in terms of objective fitness index K . At the same time, computers perform affective computing and learning algorithms, generating affective evaluations of individuals for human references.

Step 4. Select excellent individuals based on human-computer interaction.

Step 5. Perform crossover and mutation operations to generate the offspring.

Step 6. Decode and return to Step 2.

4 Case studies

4.1 Test functions

Consider a multi-objective-attribute decision-making problem consisting of three test functions characterized by following equations.

$$\begin{cases} y_1 = -a^{x+b} + c \\ y_2 = \frac{b}{x+a} + d \\ y_3 = a \sin(bx + e) \end{cases} \quad (15)$$

Specifically, decision-makers would like to attain a largest y_1 , a smallest y_2 and a most steady y_3 within a specific range $[0, 10]$ of x . It is noticed apparently that the three objective-attributes may turn out somewhat conflicting due to the commonly used parameters, a , b , c , d and e .

1) Using traditional IEC

Specify 6 generations and 8 individual species. Figs. 2 and 3 show the objective-attributes associated with the populations of initial and last generation.

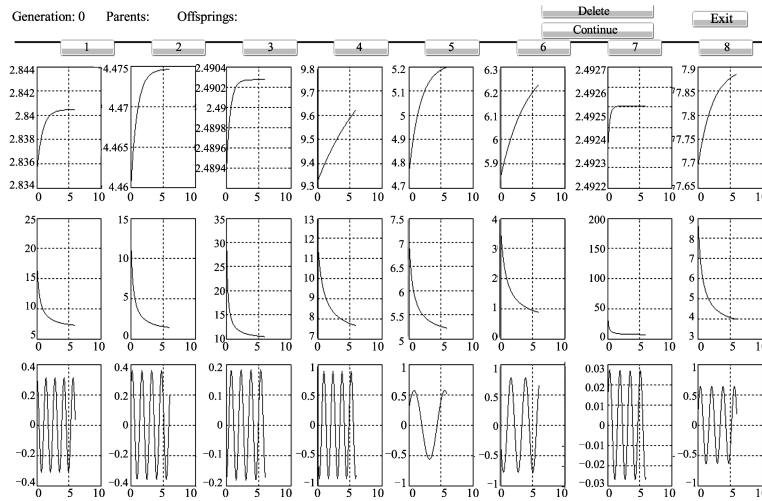


Fig. 2 Objective-attributes of the initial population

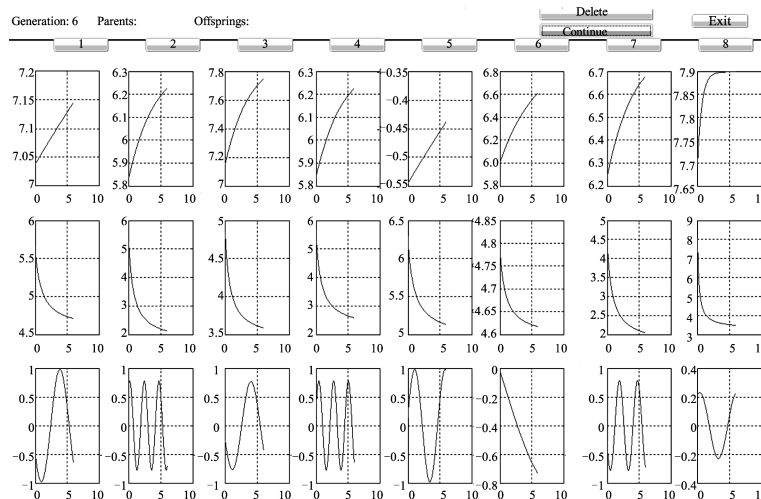


Fig. 3 Objective-attributes of the 6th population

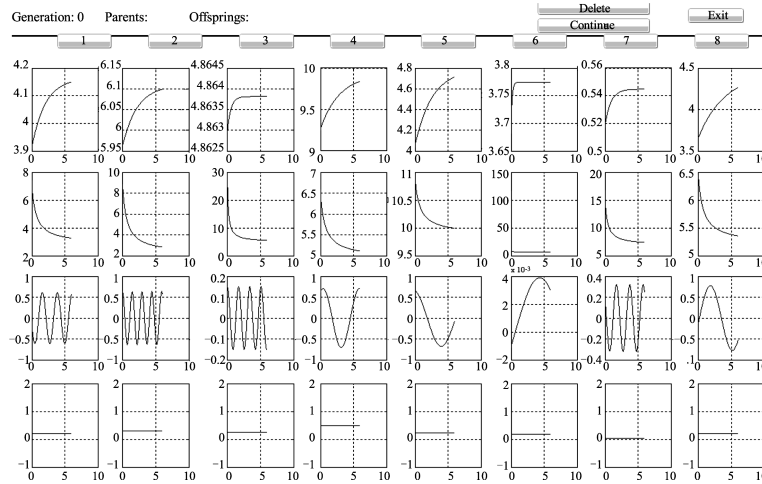


Fig. 4 Objective-attributes of the initial population based on affective interactive methods

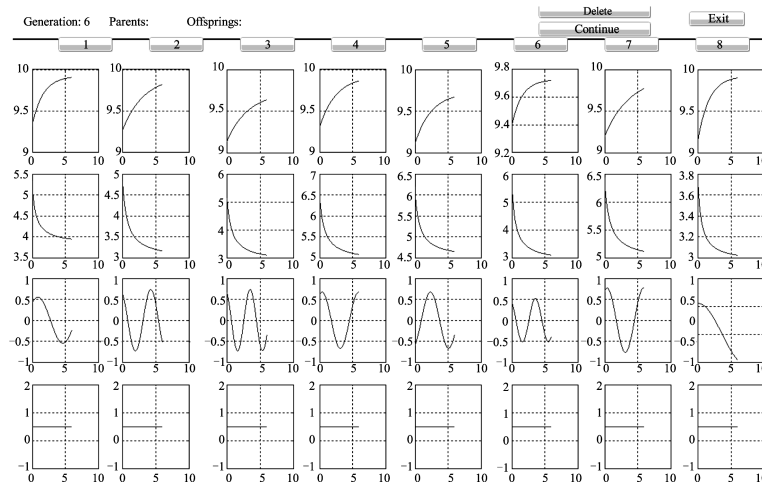


Fig. 5 Objective-attributes of the 6th population based on affective interactive methods

In Fig. 2, curves in the three rows correspond to the profiles of three objective-attributes, while diagrams in each column correspond to those of one individual. Human operators evaluate the population and select more outstanding individuals into genetic evolutions. Fig. 3 shows those of the 6th generation where the overall objective-attribute performances have been extremely improved, of course, at the expense of tough subjective work of human operators.

2) Using affective learning based IEC

Establish an objective-attribute set as:

$$\text{Property-Set} = \text{high, low, slow} \quad (16)$$

and based on Algorithm 1 (we obtain $\lambda_1 = 0.5$, $\lambda_2 = 0.167$, $\lambda_3 = 0.333$), the objective-attribute importance index is given as:

$$k_n = 0.5 \cdot \varphi_1^n + 0.167 \cdot \varphi_2^n + 0.333 \cdot \varphi_3^n \quad (17)$$

where $\varphi_1^n = \frac{p_1^n}{\hat{p}_1^n}$, $\varphi_2^n = \frac{p_2^n}{\hat{p}_2^n}$, and $\varphi_3^n = \frac{p_3^n}{\hat{p}_3^n}$, correspond to the ratios of current values with respect to desired values associated with three objective-attributes, respectively (where $\hat{p}_1^n = 11$, $\hat{p}_2^n = 0.5$, and $\hat{p}_3^n = 6.0$ are given by experts), k_n is corresponding to ∂_n in (4).

Following Algorithm 2, human-computer affective interactions are being performed. Similar to case 1), Figs. 4 and 5 display the performances of initial and 6th generation,

respectively, except that diagrams in the additional fourth row indicate the profiles of fitness, K . In addition, Figs. 6 and 7 show the profiles of affective space and average fitness K with evolutions going on. To help get access to affective learning metrics, Figs. 8 and 9 show approximations and approximating offsets with respect to human's affective preferential membership functions, respectively. Accordingly, Figs. 10 and 11 show the evolutions of adjustable parameters associated with affective computing models, A and x .

Based on different results between affective interactive learning algorithm and the traditional interactive evolutionary computation (IEC) method, the decision-making process based affective interactive learning algorithm is more objective and rapid. At the same time, by identifying the affective model (STAM) parameters A and x , the computer can grasp human's affective preference in evolutionary computation process step by step.

4.2 Parameter tuning of PID controllers

In practical process control engineering, parameter tuning of PID controllers is usually considered as a complex interactive decision-making task. As an example, Fig. 12 shows the schematic of a direct steam heater with temperature control system.

According to engineering experiences, the objective-attributes associated with PID parameter tuning are spec-

ified as three terms: overshoot that is expected as small as possible, regulating time that is expected as small as possible, and closed-loop output variance that is expected as small as possible. Practically, based on Algorithm 1 (we obtain $\lambda_1 = 0.5, \lambda_2 = 0.167, \lambda_3 = 0.333$) the objective-attribute importance index is given as:

$$k_n = 0.5 \cdot \varphi_1^n + 0.167 \cdot \varphi_2^n + 0.333 \cdot \varphi_3^n \quad (18)$$

k_n is correspond to ∂_n in (4). Set the initial affective space as $(-1, 0, 1)$. Table 1 presents key data relevant to the interactive PID parameter tuning process. Fig. 13 shows the corresponding changes of affective space in the interactive evolutions. Figs. 14 and 15 respectively display approximations and approximating offsets of affective preferential membership functions. Accordingly, Figs. 16 and 17 show the evolutions of adjustable parameters associated with affective computing models.

Based on affective interactive learning algorithm, the PID parameters tuning process is more objective and rapid than the tuning process by human's experience. At the same time, by identifying the affective model (STAM)

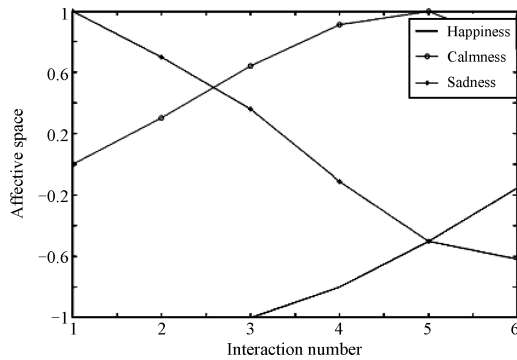


Fig. 6 Affective computing curves

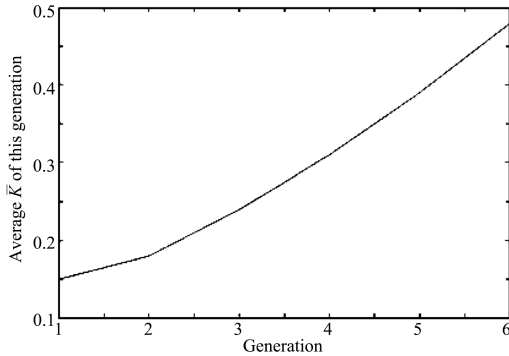


Fig. 7 Curves of \bar{K}

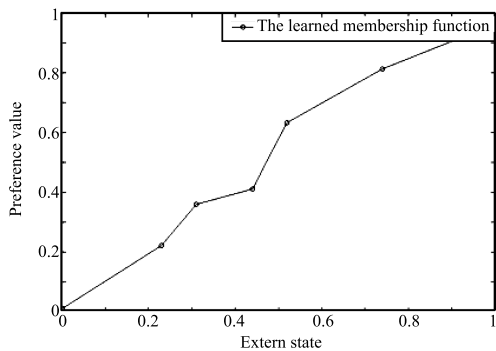


Fig. 8 Approximations of the affective preferences

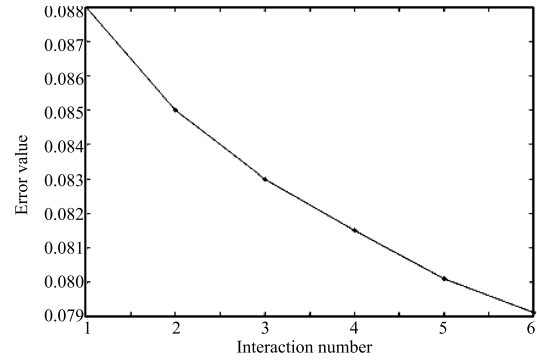


Fig. 9 Approximating offsets of the affective preferences

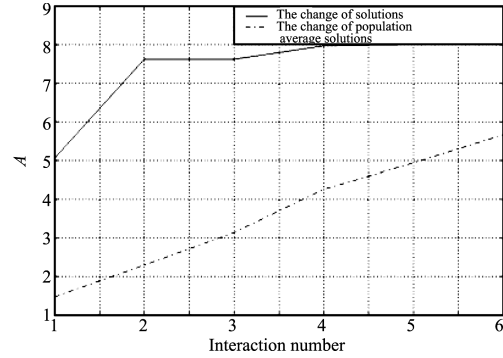


Fig. 10 Evolutions of affective parameter A

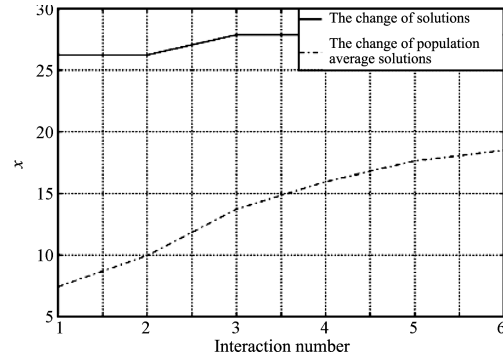


Fig. 11 Evolutions of affective parameter x

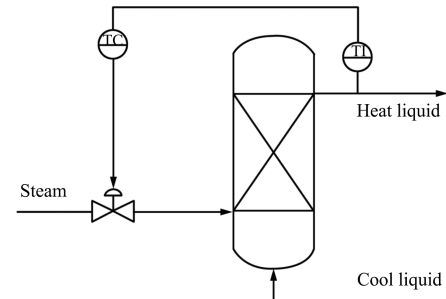


Fig. 12 A direct steam heater with temperature control system

parameters A and x , the computer can grasp human's affective preference in evolutionary computation process step by step.

5 Conclusions

Under the framework of IEC, compatible affect compu-

Table 1 Data relevant to the interactive PID parameter tuning

	PID parameter	Overshoot (%)	Transition time	Closed-loop output variance	Performance index	Affect space
1	2.5 0.1 0	35	180	0.0628	1.318648	-1.00 0.00 1.00
2	2.5 0.09 0	30	165	0.0609	1.289294	-1.00 0.20 0.80
3	2.25 0.08 0	28	153	0.0599	1.222214	-1.00 0.60 0.40
4	2.4 0.08 0	29	155	0.058	1.138846	-1.00 0.99 0.01
5	2.4 0.07 0	27	166	0.0564	1.130437	-0.70 1.00 -0.3.
6	2.4 0.05 0	26	250	0.0524	1.127317	-0.30 0.90 -0.60
7	2.4 0.03 0	25	270	0.0515	1.113593	0.20 0.80 -1.00

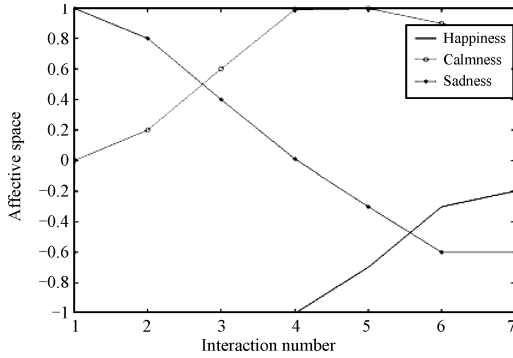


Fig. 13 Profiles of the affective space

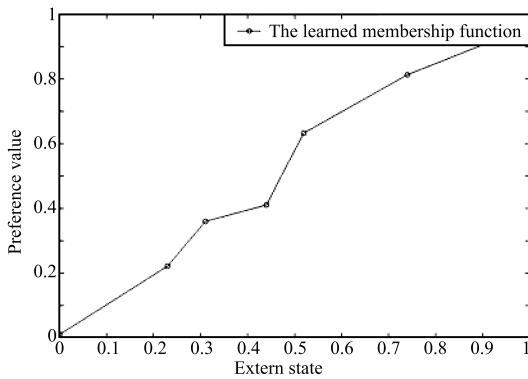


Fig. 14 Approximations of the affective preferences

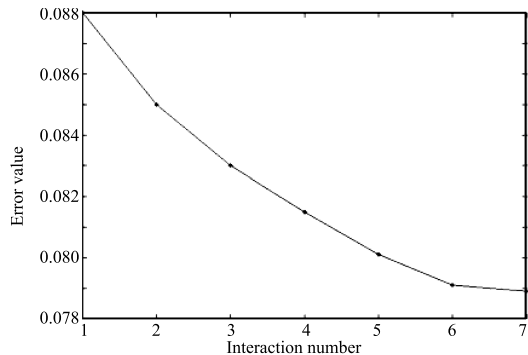


Fig. 15 Approximating offsets of the affective preferences

ting and affective learning philosophies have been extensively investigated along with enabling algorithms. In contrast to traditional IEC, the proposed approaches are recognized as able to gradually grasp essentials in human's subjective judgment in decision-making, reduce human's

subjective fatigue and make the decisions more objective and scientific. Affective learning algorithm's complexity and convergence analyses are shown in Appendixes A and B to display the algorithms' performance, Affective learning algorithm's complexity is not greater than genetic algorithms (GA) and their convergence is globally convergent. To exemplify their applications in process control engineering, we particularly provided an affective interactive evolutionary solution for PID controller tuning which is usually considered as a kind of intractable and time-consuming task. Case studies demonstrate the effectiveness and promising potentials of these contributions. Nonetheless, it should be pointed out that this research remains rather fundamental currently, and is in desperate need of further in-depth investigations on certain key issues. For example, study on problems of how to attain more appropriate subjective preferential structures in evolutions would be a potentially useful avenue for future research.

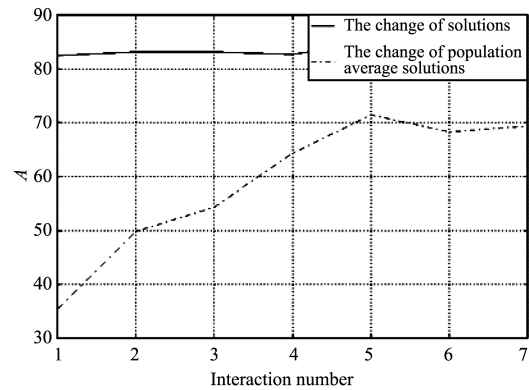


Fig. 16 Evolutions of affective parameter A

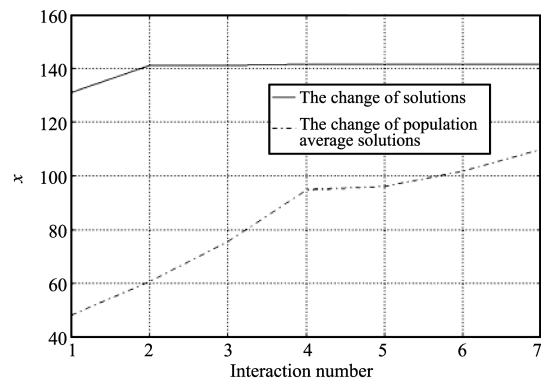


Fig. 17 Evolutions of affective parameter x

Appendix A Complexity analyses of the effective learning algorithms

As a technique of computer science, algorithm's complexity analysis is typically concerned with time and space complexity which is meant to measure the costs of the algorithm in terms of time and space. In this sense, we briefly present the complexity analysis of the affective learning algorithms as follows.

Time complexity analyses

To facilitate the discussion, initially, we specify some related parameters associated with the algorithms as follows. t denotes the number of human-computer affective interactions; $p(t)$ is the population of t th generation; m is the population size; q is the length of chromosome; p_c is the crossover rate; p_m is the mutation rate; f is the human's expectation value. Additionally, some parameters are involved in the preferential minimization problem solved by genetic algorithms as well, in which, n is the evolution number; $p'(n)$ is the population of n th generation; k is the population size; l is the length of chromosome; p'_c is the crossover rate; p'_m is the mutation rate; f' is the human's expectation value. Thus, the basic statements involved in the algorithms can be summarized as follows.

```

Initialize ( $p_c, p_m, t, f$ );
//initializing parameters of the interactive evolutionary computing algorithm (i.e., crossover rate, mutation rate etc.);
{ $t = 0$ ;
1) initialize  $p(t)$ ; //initiating population randomly;
2) calculate the multi-objective fitness index of the initial chromosome group;
3) for ( $j = 1; j < t + 1; j ++$ );
//when the fitness index of the highest chromosome fitness value is less than that of human's expectations, do as follows;
{
4) select the excellent individuals; //selection operations;
5) crossover of  $p(t)$ ; //crossover operations;
6) mutation of  $p(t)$ ; //mutation operations;
7) achieve chromosome groups,  $Q(t + 1)$ , of the next generation;
//calculating chromosome groups' multi-objective fitness index of the next generation;
8) according to affective computing metrics, calculate agent's affective preferences corresponding to each individual;
9) present human's preferences of each individual by interactions;
//next, solving the minimization problem in terms of the preferential deviation between agents and human;
{
10) initialize ( $p'_c, p'_m, n, f'$ );
//initializing parameters of the genetic algorithm (i.e., crossover rate, mutation rate etc.);
11) initialize  $p'(n)$ ; //initiating population of  $A, x$  randomly;
12) calculate fitness index;
13) for ( $i = 1; i < n + 1; i ++$ ); //when the highest fitness index is still less than the expected one, do as follows;
{
14) selection of  $p'(n)$ ; //selection operations;
15) crossover of  $p'(n)$ ; //crossover operations;
16) mutation of  $p'(n)$ ; //mutation operations;
17) achieve next generation of chromosome groups,  $Q(n + 1)$ ;
//calculating the chromosome groups' fitness index of the next generation;
}
18) update the optimized affective computing model parameters  $A, x$ ;
}
}
19) achieve the average multi-objective fitness of the current chromosome groups.

```

It is obvious that the basic statement which has the most execution time in the algorithm is usually in the innermost loop of the loop body. Taking account of statements 3) ~ 12) and 13) ~ 17) forming nested loops, the time complexity of the algorithms is eventually characterized by: $T_1(n) + T_2(n) + T_3(n) * \{T_4(n) + \dots + T_{12}(n) + T_{13}(n) * [T_{14}(n) + T_{17}(n)] + T_{18}(n)\} + T_{19}(n) = O[t * ((m * q) + n * (k * l))]$, where, O marks the time performance.

Space complexity analyses

Space complexity is concerned with the required storage space

when the algorithms execute in computers. In addition, a general discussion can be conducted on auxiliary storage unit space besides the normal memory overhead. In this sense, the affective learning algorithm's space complexity could refer to the two nested initial chromosomes' occupant space. Furthermore, other operations are conducted on the spot. As a result, the affective learning algorithm's space complexity is presented as $O(m * q + k * l)$.

Appendix B Convergence analyses of the affective learning algorithms

Affective learning algorithms use GA framework in two parts: interactive decision-making optimization and affective model parameters' identification. Therefore, in a certain assumption conditions, affective interactive learning algorithms' convergence proof is presented based on the homogeneous finite Markov chains without certain coding mode and choice strategy.

Preparation theorem: genetic algorithm's convergent in global.

Mutation, crossover and selection operations of the transition probability for:

$$P_m(x, A) = P_m(\xi_M(t) \in A | \xi(t) = x)$$

$$P_C(x, A) = P_C(\xi_C(t) \in A | \xi(t) = x)$$

$$P_S(x, A) = P_S(\xi_S(t) \in A | \xi(t) = x)$$

Therefore, $A \subset X^N$. The stationary Markov chains $\{\xi(t) : t \in Z^*\}$ of state space X^N are employed to describe the transfer probability of genetic algorithms.

$$P(x, A) = \int_y \int_z P_M(x, dy) P_C(x, dz) P_S(z, A) dy dz$$

Two sufficient preconditions will be needed to realize algorithm's global convergence: 1) The global optimal solution can be obtained in limited searching time from random initial populations; 2) Optimal operations are employed to prevent loss of optimal solutions in the search process. Therefore, we assume that the genetic operations are met the properties above.

Property B1 (Prepotency of genetic operations). For any t time, if $\xi(t) \in S_{opt}^N$, then $\xi_M(t+1) \in S_{opt}^N$; if $\xi_M(t) \in S_{opt}^N$, then $\xi_C(t+1) \in S_{opt}^N$; if $\xi_C(t) \in S_{opt}^N$, then $\xi_S(t+1) \in S_{opt}^N$.

Property B2 (Limited steps' accessibility of the search process). There is a time t_0 , for any initial population $\xi(1) = x$, any measurable subset $A \in S_{opt}^N$ and any $\delta(x) > 0$, transition probability always meets $p(1, t_0; x, A) \geq \delta(x)\phi(A)$ (where x stands for the optimization state, $\phi(\cdot)$ stands for a measure function in the measurable space, and $\phi(S_{opt}^N) = 0$).

Definition B1. Affective interactive learning algorithms' convergence includes interactive decision solution search, as well as the identification process's convergence to affective model (STAM) parameters η and x .

Theorem B1. Affective interactive learning algorithm is globally convergent.

Proof. According to Definition 4, Theorem B1 proving process includes two parts as follows:

1) $\chi_t = \{\chi_1(t), \chi_2(t), \dots, \chi_M(t)\}$ stands for the interactive decision-making solution, χ_j stands for the individuals of j generation population, $i = 1, 2, \dots, M$, M stands for the population size. $Z'_j = \max\{f(x_j(t) | j = 1, 2, \dots, M)\}$ is described as the most optimal fitness of j generation population; $f' = \max\{f'(x) | x \in S\}$ stands for the global optimal fitness, S stands for individual space, x stands for any individual in S . If interactive decision-making process is globally convergent, then $\lim_{t \rightarrow \infty} p\{Z'_t = f^*\} = 1$.

2) In addition, due to the STAM model parameter identification is still using genetic algorithm framework, parameter identification algorithm's convergence is defined as: $\eta_t = \{A_1(t), A_2(t), \dots, A_N(t)\}$ and $x_t = \{x_1(t), x_2(t), \dots, x_N(t)\}$ stand for t generation population of model STAM parameters in affective interactive learning algorithms, A_i and x_i stand for individuals of t generation population, $i = 1, 2, \dots, N$, N stands for population scale. $Z_i = \max\{f(A_i(t), x_i(t)) | i = 1, 2, \dots, N\}$ is described as the most optimal fitness in the population; $f = \max\{f(A, x) | A, x \in S\}$ is described as the global optimal fitness, S stands for the individual space, x stands for the any individual in S .

If the parameters identification process is global convergent, $\lim_{t \rightarrow \infty} p\{Z'_t = f^*\} = 1$. \square

Affective interactive learning algorithms' global convergence proof is as follows:

Theorem B2. Affective interactive decision-making process' convergence is global.

Proof. For global optimization problems of affective interactive learning algorithms, set the solution as a feasible region (whose rank is N) standing for anyone finite solution; if the population size is fixed, crossover probability $P_C \in (0, 1)$, mutation probability $P_M \in (0, 1)$ and choosing mechanism will be fixed. Reasoning process is shown as follows:

Set $P(t)$ as t generation population, $P(t) = \{a_i(t) | i \in [1, n], t \in N, a_i(t) \in I\}$, where $a_i(t)$ stands for an individual, as a feasible domain solution; $f: I \rightarrow R$ stands for fitness function; I^* is a subset of the feasible region I .

By computing the comprehensive fitness index of interactive decision solution, each subset has maximum global fitness. The best individual $a^*(t) = a_j(t) \in P(t)$ is from the first t generation population, where $a_j(t)$ belong to $f(a_j(t))$, $f(a_j(t)) \geq f(a_i(t) \in P(t))$.

Additionally, $a^*(t)$ will change randomly along with its fitness changing in mutation, crossover and selection operations. There is an $a^*(t)$ in every generation population at least, so the algorithm's global convergence is shown as follows:

$$P(\lim_{t \rightarrow \infty} a^*(t) \in I^*) = I \Rightarrow P(a^* \in \lim_{t \rightarrow \infty} P(t)) = 1$$

Also, homogeneous limited Markov chains are employed to describe the $a^*(t)$'s evolution. To reveal the convergence, the Markov chains can be simply transformed as $a^*(t)$ chain. Obviously, each state of $a^*(t)$ chain's state space S is only corresponding to each solution of feasible region, so $|S| = |I| = N$. Fitness $f(a^*(t))$ of the state of S will be in accordance with the descending order ($1 \rightarrow N$). When $t \rightarrow \infty$, $a^*(t)$ will change to S^* from any state with probability 1, that is to say $\lim_{t \rightarrow \infty} \sum_{j \in S} P_{ij}^t = 1$ ($i \in S$). \square

So, the interactive decision-making process will obtain the global optimal solution with Probability 1.

Theorem B3. Affective computing model (STAM) parameters (A and x) identification process' convergence is global.

Proof. Similarly, we can obtain: GA algorithms are employed to search global optimal solution in parameters (A and x) identification process ($\min \sum_{i=1}^n [\mu(x_i) - \mu'(x_i)]^2$ ($i = 1, \dots, n$)). When $t \rightarrow \infty$, $a^*(t)$ will change to S^* from any state probability. \square

Global convergence of affective interactive decision making process and affective computing model (STAM) parameters identification process are proved. So, overall affective interactive learning algorithm is globally convergent.

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