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PID Tuning Method Using Single-Valued Neutrosophic Cosine Measure and Genetic Algorithm

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ABSTRACT
Because existing proportional-integral-derivative (PID) tuning method using similarity measures of single-valued neutrosophic sets (SVNSs) and an increasing step algorithm shows its complexity and inconvenience, this paper proposes a PID tuning method using a cosine similarity measure of SVNSs and genetic algorithm (GA) to improve the existing PID tuning method. In the tuning process, the step response characteristic values (rising time, settling time, overshoot ratio, undershoot ratio, peak time, and steady-state error) of the control system are converted into the single-valued neutrosophic set (SVNS) by the neutrosophic membership functions (Neutrosophication). Then the values of three appropriate parameters in a PID controller can be determined by GA corresponding to the maximum similarity measure value between the actual (real) single-valued neutrosophic set (SVNS) and a previously determined ideal SVNS. Finally, the proposed method is tested on two actual examples, and then the simulation results show the effectiveness and convenience of the proposed PID tuning method.

KEYWORDS: Single-valued neutrosophic set; PID tuning; Cosine similarity measure; Genetic algorithm

1 INTRODUCTION

THE proportional-integral-derivative (PID) controllers have been wildly applied in various industrial fields due to its robustness, easy design, high accuracy, rapid system response, and high stability (Shahrokhi & Zomorrodi, 2003; Hussain et al., 2014). In a PID controller, there are three parameters Kp, Ki, and Kd, which must be tuned to obtain the satisfactory control performance. Then the tuning method of the PID parameters is very important in the design of the PID controller because the three parameters will affect the control performance in a control system. In general, PID tuning methods can be divided into two main classes: closed-loop and open-loop methods, such as a Ziegler–Nichols closed-loop method and a Cohen–Coon open-loop method. In software-based PID tuning methods, genetic algorithm (GA), particle swarm optimization (PSO), and fuzzy logic approaches have been usually used in existing research topics for the PID tuning (Malleham and Rajani, 2006; Bagis, 2007; Solihin et al., 2011).

As a subclass of a neutrosophic set (Smarandache, 1998), a single-valued neutrosophic set (SVNS) introduced by Smarandache, (1998) and Wang et al. (2010) can describe truth, indeterminate, and falsity degrees independently by a truth-membership function, an indeterminacy-membership function, and a falsity-membership function, that lie within the real interval [0, 1]. Today, SVNSs have been applied mainly in decision making, fault diagnosis, medical diagnosis, robot control, and so on (Gal et al., 2016; Peng et al., 2014; Liu & Wang, 2014; Ye, 2014, 2015, 2017; Mondal and Pramanik., 2015; Biswas et al., 2016; Sahin and Liu, 2016; Pramanik et al., 2017). In a control system, the unit step response characteristics of the control system corresponding to setting the PID parameters can result in "good" or "bad" or "uncertain/indeterminate" ("neither good nor bad") outcome, where "good", "medium", and 'bad'' can be considered as the truth value (T), the indeterminate value (I), and the falsity value (F), respectively, in the concept of SVNS. Therefore, from this view of point, SVNSs can describe the control performance of a system. Recently, a PID tuning method based on the single-valued neutrosophic similarity measures like

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the set-theoretic, Hamming, Euclidean, Jaccard, Dice measures was proposed for adjusting PID parameters by an increasing step algorithm (Can & Ozguven, 2017), where it did not consider the performance indexes such as the integral of the absolute value of the error (IAE) and of the square value of the error (ISE), the integral of the time weighted absolute value of the error (ITAE), and the integral of the time weighted square of the error (ITSE) (Shahrokhi & Zomorrodi, 2003) and instead used the time-domain step response characteristics like rising time, settling time, overshoot ratio, undershoot ratio, peak time, and steady-state error. In this method, firstly it is necessary to know rough ranges of Kp, Ki, and Kd values based on a Ziegler–Nichols tuning method. Then in the search algorithm, the Kp, Ki, and Kd values were increased one by one from a given lower value to an upper value, which is called a increasing step algorithm. At the end of each step, the step response characteristic values of the control system were conversed into a SVNS by the three neutrosophic membership functions (Neutrosophication). Finally, the values of appropriate PID parameters can be determined according to the maximum similarity measure value between an actual (real) SVNS and the previously determined ideal SVNS, which was found from the measure value array obtained in all operational steps. However, this PID tuning method shows its complexity and inconvenience in the increasing step algorithm and lacks an investigation of the cosine similarity measure of SVNSs. To overcome these drawbacks, this paper proposes an improved PID tuning method by using the cosine similarity measure of SVNSs and GA as the improvement and complement of the existing method. This improved PID tuning method can directly tune the three parameters of a PID controller and obtain satisfactory control requirements.

The rest of this paper is constructed as follows. Section 2 briefly describes some concepts of SVNSs and a cosine similarity measure of SVNSs. Section 3 presents a PID tuning method based on the cosine measure of SVNSs and GA. Two illustrative examples and a comparative analysis are provided in Section 4. Section 5 contains conclusions and future research.

2 SVNS AND ITS COSINE MEASURE

SVNSs introduced in the real standard interval [0, 1] are usually used for real applications of science and engineering fields as a subclass of neutrosophic sets (Smarandache, 1998; Wang et al., 2010), which can describe uncertain/indeterminate and inconsistent information that fuzzy sets and intuitionistic fuzzy sets cannot express. Then, SVNS can be defined below.

Definition 1 (Smarandache, 1998; Wang et al., 2010). A SVNS S in a universe of discourse U can be expressed as $S = \{\langle u, T_S(u), I_S(u), F_S(u)\rangle \mid u \in U\}$, which is characterized by a truth-membership function TS(u), an indeterminacy-membership function IN(u) and a falsity-membership function FS(u) independently and the sum of TS(u), IS(u), FS(u) ∈ [0, 1] is 0 ≤ TS(u) + IS(u) + FS(u) ≤ 3 for each u in U.

For convenience, a basic element $\langle u, T_S(u), I_S(u), F_S(u)\rangle$ in S is denoted by u = (T, I, F) for short, which is called a single valued neutrosophic value (SVNV).

Assume that u1 = (T1, I1, F1) and u2 = (T2, I2, F2) are two SVNVs. Then, the basic relations for SVNVs u1 and u2 are defined as follows (Wang et al., 2010):

(1) Inclusion: u1 ⊆ u2 if and only if T1 ≤ T2, I1 ≥I2, F1 ≥ F2;
(2) Equality: u1 = u2 if and only if u1 ⊆ u2 and u2 ⊆ u1;
(3) Complement: $u_1^c = (F_1, 1 - I_1, T_1)$;
(4) Union: u1∪u2 = (T1 ∨ T2, I1 ∧ I2, F1 ∧ F2);
(5) Intersection: u1∩u2 = (T1 ∧ T2, I1 ∨ I2, F1 ∨ F2).

Based on the cosine function, Ye (2015) proposed the cosine measure of SVNSs and gave the following definition:

Definition 2 (Ye, 2015). Let S1 = {u11, u12, …, u1n} and S2 = {u21, u22, …, u2n} be two SVNSs, where u1i = (T1i, I1i, F1i) and u2i = (T2i, I2i, F2i) (i = 1, 2, …, n) are the i-th SVNVs of S1 and S2, respectively. Then, the cosine similarity measure between S1 and S2 is defined as

$$Cs(S_1, S_2) = \frac{1}{n}\sum_{i=1}^{n}\cos\left[\frac{\pi}{6}\left(|T_{1i} - T_{2i}| + |I_{1i} - I_{2i}| + |F_{1i} - F_{2i}|\right)\right]. \quad (1)$$

Then, the cosine measure contains the following properties (Ye, 2015):

(S1) 0 ≤ Cs(S1, S2) ≤ 1;

(S2) Cs(S1, S2) = 1 if and only if S1 = S2, i.e., u1i = u2i for i = 1, 2, …, n;

(S3) Cs(S1, S2) = Cs(S2, S1);

(S4) If S1 ⊆ S2 ⊆ S3 for the SVNS S3, then Cs(S1, S3) ≤ Cs(S1, S2) and Cs(S1, S3) ≤Cs(S2, S3).

3 PID TUNING METHOD WITH THE COSINE MEASURE AND GENETIC ALGORITHM

THIS section proposes an improve PID tuning method, where the cosine similarity measure of SVNSs and GA are used to determine PID parameters, as the improvement and complement of existing PID tuning method (Can & Ozguven, 2017).

3.1 PID controller

PID control is a feedback controller, which is usually applied to industrial control systems. A typical block diagram of the PID control system is shown in Figure 1.

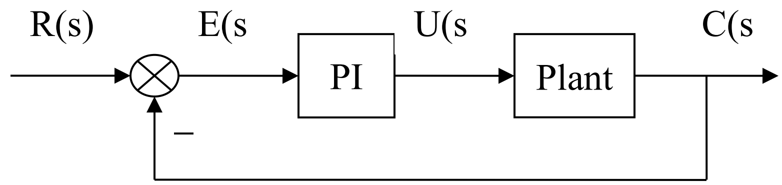

Figure 1. PID control system

Then, the output of the PID controller in the time domain is expressed as

$$u(t) = K_p e(t) + K_i \int_0^t e(t)dt + K_d de(t)/dt, \tag{2}$$

where $e(t) = r(t) - c(t)$ is a control error, K_p, K_i, and K_d are three basic parameters, which are called proportional, integral, derivative parameters, respectively.

By the Laplace transform of Eq. (2), the output of the PID controller in the time domain is transformed into the output of the PID controller in the s domain:

$$U(s) = E(s)(K_p + \frac{K_i}{s} + K_d s), \tag{3}$$

In a PID control system, the setting of the three basic parameters K_p, K_i, and K_d is very important in the PID controller design, which is called PID tuning, since these basic parameters can affect the performance of the control system. Hence, it is necessary how to find a group of optimal parameters for the optimal control. As mentioned above, since the existing PID tuning method based on neutrosophic similarity measures and an increasing step algorithm shows its complex algorithm and inconvenience of tuning parameters and lacks an investigation of the cosine similarity measure, we need to propose a PID tuning method combined with a single-valued neutrosophic cosine measure and GA as the improvement and complement of the existing PID tuning method in (Can & Ozguven, 2017).

3.2 Netrosophication and similarity measure of control performance indices

In a netrosophication process (Can & Ozguven, 2017), we select rise time, settling time, percentage overshoot ratio, percentage undershoot ratio, peak time, and steady-state error values as transient state characteristics of the control system because these characteristic values can indicate the step response performance indexes of the control system. Therefore, the target unit step values are compared with the required control characteristic values to determine the suitable PID parameters. Then, similarity measures can be evaluated as the closeness between the six transient state features of the system (rise time, settling time, percentage overshoot rate, percentage undershoot rate, peak time, and steady-state error) and the desired (ideal) transient state features. The unit step response characteristics of the control system can be obtained by using MATLAB's "stepinfo" function, and then the membership functions of the control system response characteristics are directly transformed into the values of the truth, indeterminacy and falsity membership degrees.

In some case, triangle and trapezoid membership functions are used for the netrosophication process (Can & Ozguven, 2017). Thus, we consider the six transient state features: (1) C_1: rising time (s), (2) C_2: settling time (s), C_3: overshoot ratio (%), (4) C_4: undershoot ratio (%), (5) C_5: peak time (s), and (6) C_6: steady-state error, as a characteristic set $C = \{C_1, C_2, C_3, C_4, C_5, C_6\}$. The types of membership functions and their range of T_i, I_i, and F_i ($i = 1, 2, \ldots, 6$) values in a SVNS S may be determined from actual applications. By the membership functions in Fig. 2, the SVNS S is obtained as follows:

$S = \{<C_1, T_1, I_1, F_1>, <C_2, T_2, I_2, F_2>, <C_3, T_3, I_3, F_3>, <C_4, T_4, I_4, F_4>, <C_5, T_5, I_5, F_5>, <C_6, T_6, I_6, F_6>\}$.

Then the ideal SVNS S^* (desired characteristic values) can be determined as follows:

$S^* = \{<C_1, 1, 0, 0>, <C_2, 1, 0, 0>, <C_3, 1, 0, 0>, <C_4, 1, 0, 0>, <C_5, 1, 0, 0>, <C_6, 1, 0, 0>\}$.

Therefore, the cosine measure between S and S^* can be defined as

$$Cs(S, S^*) = \frac{1}{6}\sum_{i=1}^{6} \cos\left[\frac{\pi}{6}(1 - T_i + I_i + F_i)\right]. \tag{4}$$

Obviously, the larger the value of $Cs(S, S^*)$, the better the control performance.

3.3 Genetic algorithm

GA can be used to solve a wide range of optimization problems (Goldberg, 1989). A series of typical routines are included in this optimization process. To obtain the optimal control performances for the PID control system, as an optimization problem of the minimum function value, we can establish the following fitness function:

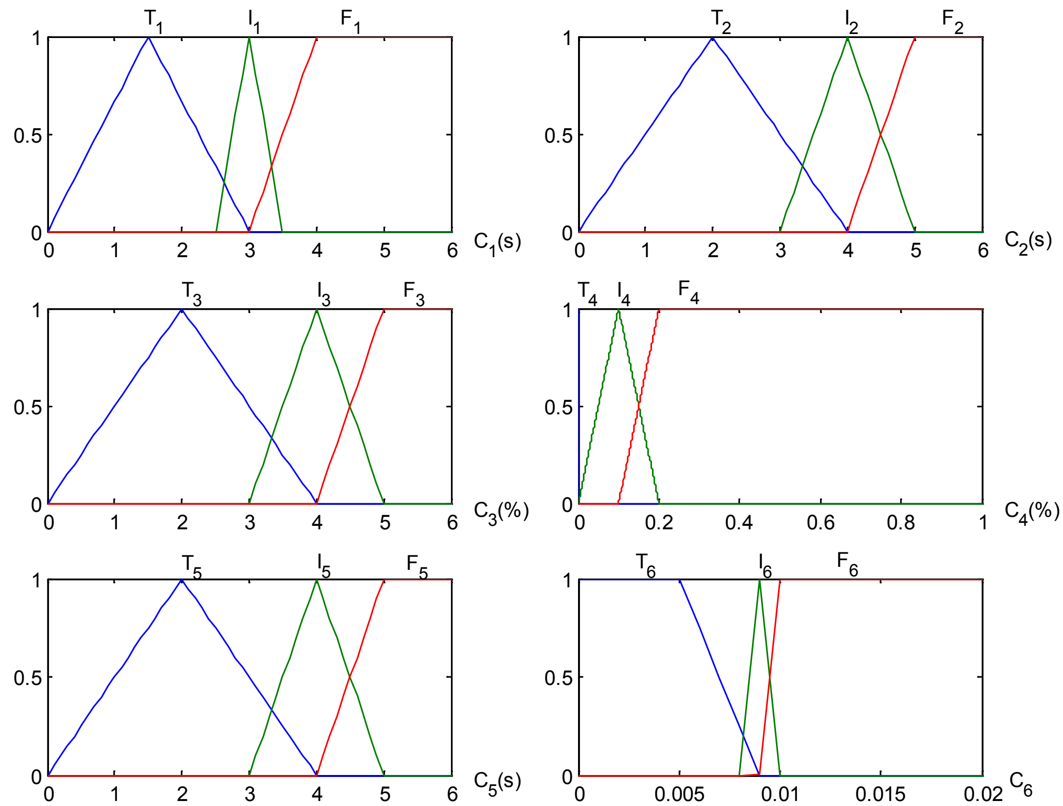

Figure 2. The membership functions of six transient state characteristics. C1: rising time (s), C2: settling time (s), C3: overshoot ratio (%), C4: undershoot ratio (%), C5: peak time (s), and C6: steady-state error.

$$f = 1 - Cs(S, S^*) . \quad (5)$$

Then, we use real values coding for the three parameters K_p. K_i, K_d in the PID controller. In general, GA is included in the following typical process:

Initial population: random sets of N solutions are generated as initial sets of K_p, K_i and K_d values.

Evaluation: the entire population of real values coding will be evaluated by their fitness values calculated from an objective function.

Selection: the high fitness value of an individual will be generated in successive generations, where the best individual is kept and only replaced in successive generations when a better individual is found. The partial population of individuals is chosen to use new population of individuals for the next generation.

Crossover: the exchange of the information between two or more individuals is provided as crossover according to the crossover probability *Pc*.

Mutation: the compositions of a few randomly chosen real values coding are changed with a small probable mutation corresponding to the mutation probability *Pm*.

Terminal condition: the search process of GA terminates as the final K_p, K_i and K_d values when the convergence or desired requirement is reached.

The flow chart of the above GA process is shown in Figure 3.

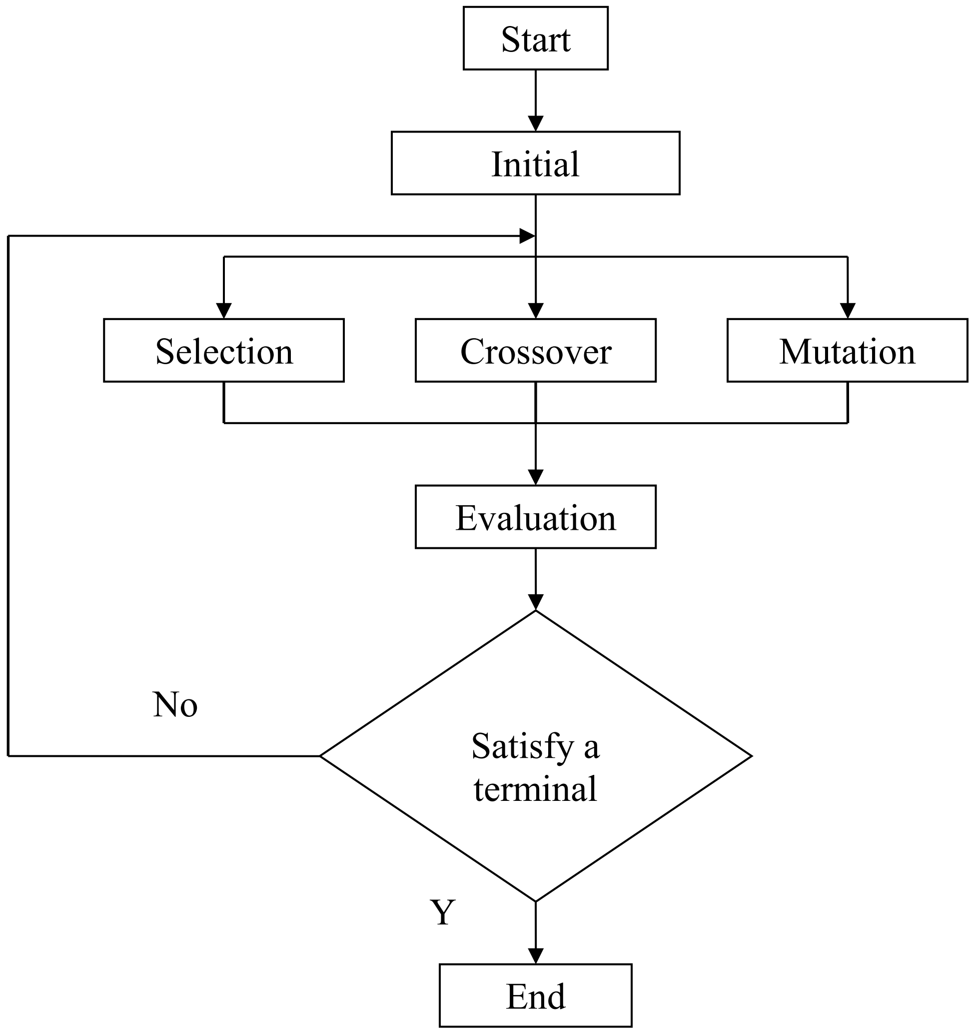

Figure 3. The flow chart of GA

4 ILLUSTRATIVE EXAMPLES AND COMPARATIVE ANALYSIS

4.1 Illustrative example 1

TO demonstrate the effectiveness of the proposed method, the simulation experiment is tested by the following open-loop transfer function:

$$G_1(s) = \frac{20}{(0.4s+1)(4s+5)}. \quad (6)$$

In the simulation experiment, we use real values coding for the three parameters K_p, K_i and K_d in the search process of GA, where the GA parameters applied for the simulation are considered as $1 \le K_p \le 30$, $0 \le K_i \le 30$, and $0 \le K_d \le 30$, the population size $N = 20$, the crossover probability $Pc = 0.9$, the mutation probability $Pm = 0.1$, and the terminal condition $f = 0.017$. The step response curve is drawn in Fig. 4 for the final K_p, K_i, and K_d values at the terminal step of GA. In the meantime, the maximum measure value obtained from $Cs(S, S^*)$ and corresponding values of the PID parameters are shown in Table 1, and then step response characteristics for G_1(s) corresponding to the obtained K_p, K_i, K_d values are indicated in Table 2.

Table 1 **The maximum cosine measure value and tuning values of the PID parameters for $G_1(s)$**

Measure method	Measure value	Step	K_p	K_i	K_d
Cosine measure	0.9833	42	1.9122	1.0635	0.9517

Table 2 **Step response characteristics for $G_1(s)$ based on the cosine measure and GA**

Step response characteristics	Step response characteristic values
Rising time (s)	0.2182
Settling time (s)	2.0902
Overshoot rate (%)	2.0724
Undershoot rate (%)	0
Peak time (s)	1.8055
Steady-state error	0

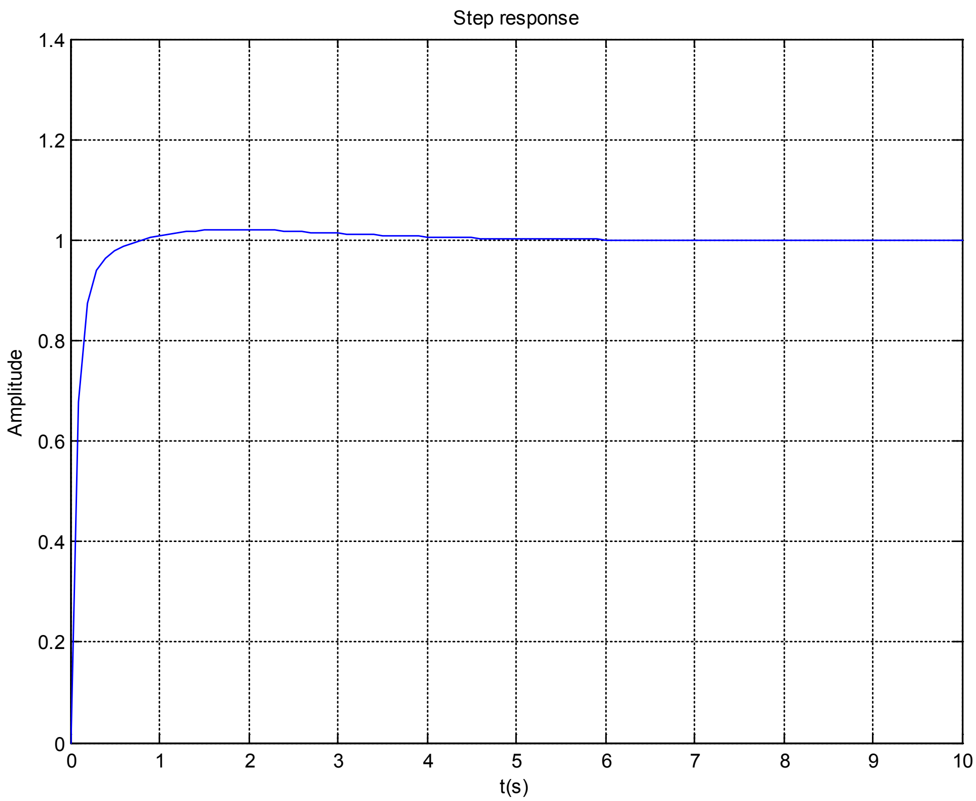

Figure 4. **Step response for $G_1(s)$ based on the cosine measure and GA**

In Table 1, the maximum cosine similarity measure value is 0.9833 at the 42-th step in the GA operation corresponding to K_p = 1.9122, K_i = 1.0635, and K_d = 0.9517, and then Table 2 and Fig. 4 shows the corresponding step response values and curve, respectively, with the desired control performances. These results demonstrate the effectiveness and rationality of the proposed method since the cosine similarity measure value is very close to 1. Therefore, this PID tuning method can realize multiple criteria control requirements (desired step response characteristics), which is its advantage; while the conventional PID tuning methods (Shahrokhi & Zomorrodi, 2003; Malleham & Rajani, 2006; Bagis, 2007; Solihin et al., 2011; Hussain et al., 2014) may not reach these control requirements.

4.2 Illustrative example 2

For convenient comparison, an illustrative example is adapted from the literature (Can & Ozguven, 2017) to demonstrate the effectiveness and advantage of the proposed method.

The proposed method is tested in the following quadratic open-loop transfer function (Can & Ozguven, 2017):

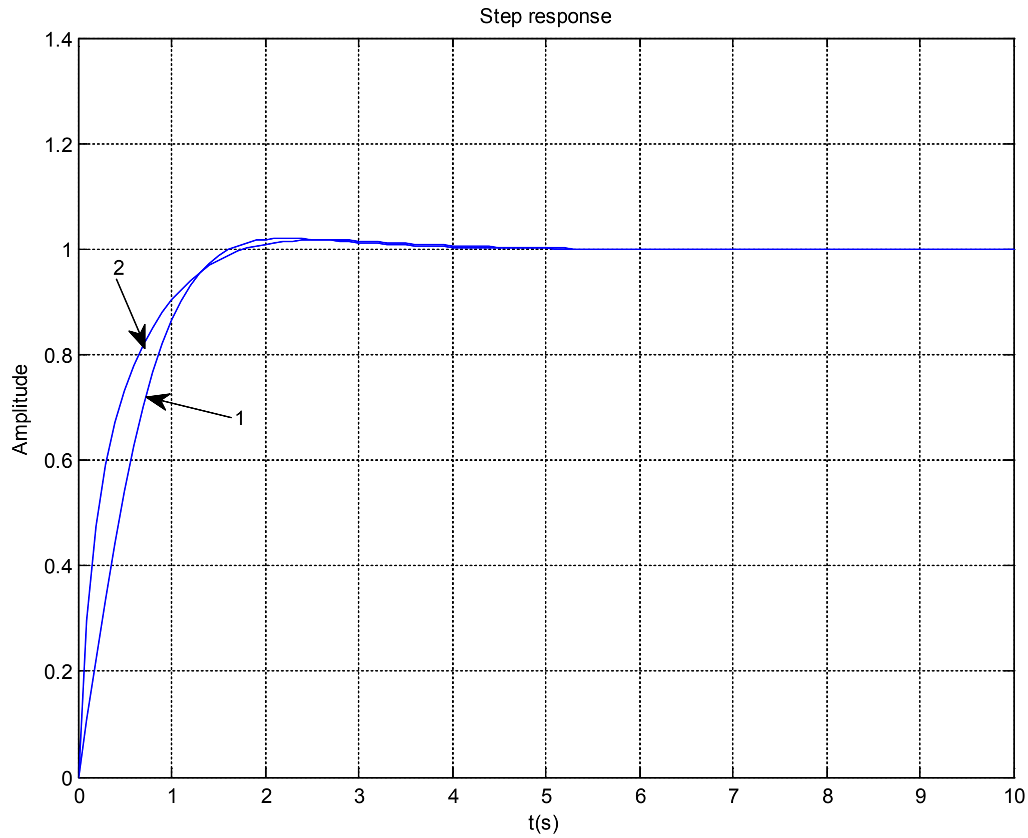

Fig. 5 Step response for $G_2(s)$ using the proposed method and the existing method (Can & Ozguven, 2017).

$$G_2(s) = \frac{1}{(s+1)(s+4)}. \quad (7)$$

By using the same parameters and the same membership functions as in the first example, the step response curve is drawn in Fig. 5 according to the final K_p, K_i, and K_d values at the terminal condition $f = 0.007$ in the GA operation. Then, all the results obtained by the proposed PID tuning method are shown in Table 3 and Table 4.

For comparative convenience, all the results obtained by the PID tuning method in the literature (Can & Ozguven, 2017) are also shown in Table 3, Table 4, and Fig. 5, where the PID tuning method in (Can & Ozguven, 2017) used the set-theoretic, Hamming, Euclidean, Jaccard, Dice measures by the search algorithm increased one by one (called increasing step algorithm) around the K_p, K_i, and K_d Ziegler–Nichols values from given lower values to upper values.

Curve 1 is the PID tuning method based on the set-theoretic, Hamming, Euclidean, Jaccard, Dice measures and increasing step algorithm (Can & Ozguven, 2017) and Curve 2 is the PID tuning method based on the cosine measure and GA.

In Tables 3 and 4, the proposed method obtains the maximum cosine measure value (0.9933) at the 34-th step in the GA operation and the corresponding three parameters K_p = 12.4693, K_i = 11.7133, and K_d = 3.8330 and step response characteristic values for the transfer function $G_2(s)$. In the meanwhile, Curve 2 in Fig. 5 shows the step response curve drawn according to the obtained PID parameters at the 34-th step. Then, Curve 1 in Fig. 5 shows the step response curve drawn according to the parameters K_p = 8, K_i = 8, and K_d = 1 obtained at the 12771-th step based on the set-theoretic, Hamming, Euclidean, Jaccard, Dice measures and increasing step algorithm.

4.3 Comparative analysis

Let us compare the proposed method using the cosine measure and GA with the existing method using the set-theoretic, Hamming, Euclidean, Jaccard, Dice measures and increasing step algorithm (Can & Ozguven, 2017). In Table 3, the cosine measure value is maximal in all measure values, and then the operational steps in the proposed method are the smallest in all operations. However, the existing

Table 3. The maximum values obtained from various similarity measures and the corresponding tuning values of the PID parameters for $G_2(s)$

Measure method	Measure value	Step	K_p	K_i	K_d
Hamming	0.9183	12771	8	8	1
Euclidean	0.8719	12771	8	8	1
Set-theoretic	0.911	12771	8	8	1
Jaccard	0.9729	12771	8	8	1
Dice	0.9855	12771	8	8	1
Cosine	0.9933	34	12.4693	11.7133	3.8330

Table 4 Step response characteristics for $G_2(s)$ based on various measures

Step response characteristics	Set-theoretic, Hamming, Euclidean, Jaccard, Dice measures and increasing step algorithm (Can & Ozguven, 2017)	Cosine measure and GA
Rising time (s)	1.0027	0.9597
Settling time (s)	2.3000	1.5095
Over shoot (%)	2.0152	1.7056
Undershoot (%)	0	0
Peak time (s)	2.2295	2.5716
Steady-state error	0	0

method in (Can & Ozguven, 2017) needs to find out the maximum measure value at the 12771-th order from the measure value array in all calculation steps (about 40000 steps), while the improved method can directly find out the maximum measure value at the 34-th step. The values in Table 4 and Curves 1 and 2 in Fig. 5 demonstrate that the settling time and overshoot rate of the proposed method are obviously superior to those of the existing method (Can & Ozguven, 2017) in the unit step responses of the system. Because the improved PID tuning method use GA (heuristic search) instead of the increasing step algorithm (Can & Ozguven, 2017) to narrow down the search range for the appropriate PID coefficients as the improvement of the existing search method, the main advantages of the proposed method are simple and effective in the PID tuning process to search for the suitable K_p, K_i, and K_d values in the PID controller. The combination of the single-valued neutrosophic cosine similarity measure and GA can be used for the PID tuning. Obviously, the improved PID tuning method is more effective and convenient than the PID tuning method introduced in (Can & Ozguven, 2017).

5 CONCLUSION

DUE to the complexity and inconvenience of the existing method for searching for suitable PID parameters based on the neutrosophic similarity measures and increasing step algorithm, this paper introduced an improved PID tuning method based on the cosine measure of SVNSs and GA for searching for suitable PID parameters to overcome the drawbacks of the existing method in the PID tuning process. Then, the test results carried out on two illustrative examples demonstrated the effectiveness and convenience of the improved PID tuning method, and then the PID control performances are superior to the ones given in (Can & Ozguven, 2017). The main advantage of the improved method is that it does not require any complex calculations and can rapidly tune the PID parameters according to multiple criteria control requirements (desired step response characteristics). In future research, we shall further improve existing PID tuning method and extend it to real time control systems with neutrosophic information, and also shall investigate the refined SVN (Smarandache, 2013) cosine measure and genetic algorithm for PID tuning.

6 REFERENCES

Bagis, A. (2007). Determination of the PID controller parameters by modified genetic algorithm for improved performance. *Journal of Information Science and Engineering*, 23, 1469–1480.

Biswas, P., Pramanik, S., Giri, B.C. (2016). TOPSIS method for multi-attribute group decision-making under single valued neutrosophic environment. *Neural Computing and Applications*, 27(3), 727-737.

Biswas, P., Pramanik, S., Giri, B.C. (2016). Value and ambiguity index based ranking method of single-valued trapezoidal neutrosophic numbers and its application to multi-attribute decision making. *Neutrosophic Sets and Systems*, 12, 127-138.

Can, M.S., Ozguven, O.F. (2017). PID tuning with neutrosophic similarity measure. *International Journal of Fuzzy Systems*, 19(2), 489–503.

Goldberg, D.E. (1989). Genetic algorithms in Search, Optimization, and Machine Learning. Addison-Wesley Professional.

Gal, A., Vladareanu, L., Smarandache, F., Yu, H., Deng, M. (2016). Applications of neutrosophic logic approaches in ''RABOT'' real time control. *Neutrosophic Theory and Its Applications*. Collected Papers, I, pp. 55-60

Hussain, K.M., Zepherin, R.A.R., Kumar, M.S., Kumar, S.M.G. (2014). Comparison of PID controller tuning methods with genetic algorithm for FOPTD system. *International Journal of Engineering Research and Applications*, 4(2), 308–314.

Liu, P.D., Wang, Y.M. (2014). Multiple attribute decision making method based on single valued neutrosophic normalized weighted Bonferroni mean, *Neural Computing and Applications*, 25(7), 2001-2010.

Malleham, G., Rajani, A. (2006). Automatic tuning of PID controller using fuzzy logic. The 8th International Conference on Development and Application Systems, Suceava, Romania, pp. 120-127.

Mondal, K., Pramanik, S. (2015). Neutrosophic tangent similarity measure and its application to multiple attribute decision making. *Neutrosophic Sets and Systems*, 9, 85-92.

Peng, J.J., Wang, J.Q., Zhang, H.Y., Chen, X.H. (2014). An outranking approach for multi-criteria decision-making problems with simplified neutrosophic sets. *Applied Soft Computing*, 25, 336–346.

Pramanik, S., Biswas, P., Giri, B.C. (2017). Hybrid vector similarity measures and their applications to multi-attribute decision making under neutrosophic environment. *Neural Computing and Applications*, 28(5), 1163–1176.

Smarandache, F. (1998). Neutrosophy. Neutrosophic Probability, Set, and Logic, Amer. Res. Press, Rehoboth, USA.

Shahrokhi, M., Zomorrodi, A. (2003). Comparison of PID controller tuning methods. Proceedings of 8th National Iranian Chemical Engineering Congress, Ferdowsi University, Mashhad.

Solihin, M.I., Tack, L.F., Kean, M.L. (2011). Tuning of PID controller using particle swarm optimization (PSO). Proceeding of the International Conference on Advanced Science, Engineering and Information Technology, Malaysia, pp. 458-461.

Smarandache, F. (2013). *n-Valued refined neutrosophic logic and its applications in physics*. *Progress in Physics*, 4, 143-146.

Sahin, R., Liu, P. (2016). Maximizing deviation method for neutrosophic multiple attribute decision making with incomplete weight information. *Neural Computing and Applications*, 27(7), 2017–2029.

Wang, H., Smarandache, F., Zhang, Y.Q., Sunderraman, R. (2010). Single valued neutrosophic sets. *Multispace and Multistructure*, 4, 410-413.

Ye, J. (2014). Multiple attribute group decision-making method with completely unknown weights based on similarity measures under single valued neutrosophic environment. *Journal of Intelligent and Fuzzy Systems*, 27(12), 2927–2935.

Ye, J. (2015). Improved cosine similarity measures of simplified neutrosophic sets for medical diagnoses. *Artificial Intelligence in Medicine*, 63(3), 171–179.

Ye, J. (2017). Single valued neutrosophic similarity measures based on cotangent function and their application in the fault diagnosis of steam turbine. *Soft Computing*, 21(3), 817–825.

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