Control System Design via Constraint Satisfaction using Convolutional Neural Networks and Black Hole Optimization

Saber Yaghoobi[a] and M. Sami Fadali[b]
Department of Electrical and Biomedical Engineering, University of Nevada, Reno, U.S.A.

Keywords: Bouc-Wen Hysteresis Model, Constraint Satisfaction Problem, Control System Design, MBH Optimization Algorithm, Deep Learning, PID Controller.

Abstract: This paper proposes a new approach to control system design through solving a Constraint Satisfaction Problem (CSP) using artificial intelligence, first using a genetic algorithm then using a Convolutional Neural Network (CNN). The genetic algorithm determines the feasible controller parameters by minimizing a cost function subject to inequality design constraints. The CNN-finds the parameters by designing a deep neural network. It is shown that the evolutionary optimization algorithm converges almost surely to the optimal solution. To demonstrate the methodologies, they are applied to the design of PID controllers for linear and nonlinear systems. Two examples are presented, an armature-controlled DC motor and Bouc-Wen nonlinear hysteresis model. Simulations results show that the proposed methods yield solutions that satisfy design specifications.

1 INTRODUCTION

Many problems in science and engineering can be posed as a constraint satisfaction problem with constraints that guarantee a desirable solution (Tsang, 2014). The solution, or set of solutions, is a set of values that satisfy all the constraints and the region of acceptable solutions is known as the feasible region. Because of complex nature of CSPs, the solution requires a mixture of combinatorial and heuristics search. One of the fields that focuses on dealing with CSPs is constraint programming (CP) (Lecoutre, 2009). Other fields of research that present solutions as CSPs are Mixed Integer Programming (Alfa et al., 2016), Satisfiability Modulo Theories (Barret and Tinelli, 2018), Answer Set Programming (Lifschitz, 2019), and Boolean Satisfiability Problem (Ohrimenko, 2007).

CSP algorithms can be divided into three different classes: backtracking search (Wu & Van Beek, 2007); constraint propagation (Bessiere, 2007); and structure-driven algorithms (Dechter & Rossi, 2006). Algorithms that utilize different versions of backtracking search construct a solution by extending a partial instantiation, step by step. While applying intelligent backtracking strategies these algorithms rely on different heuristics in order to avoid getting trapped in dead ends. Constraint propagation algorithms eliminate non-solution elements from the search space to reduce the solution space. This strategy can be used as a pre-process for the problem before using a search algorithm, or used within the search algorithm to boost its performance. Structure-driven algorithms use the structure of the primal or dual graph of the problem at hand. Structure-based methods can also be coupled with other types of algorithms to solve CSPs (Ruttkay, 1998).

Several decades ago, Zakian and Al-naib proposed a new approach to control system design by numerical solution of a set of inequalities (Zakian & Al-Naib, 1973; Zakian, 1979; Zakian, 1996; Zakian, 2005). The inequalities provided constraints on standard performance criteria, such as percentage overshoot and settling time, and the solution of the CSP yielded good controller designs. As part of his methodology, Zakian introduced the principle of matching so as to select the design constraints that guarantee that the system will match its environment (Zakian, 1996; Zakian, 2005; Zakian 1991). Zakian's approach, known as the method of inequalities or

[a] https://orcid.org/ 0000-0002-4859-5707
[b] https://orcid.org/ 0000-0002-3865-2499

Yaghoobi, S. and Fadali, M.
Control System Design via Constraint Satisfaction using Convolutional Neural Networks and Black Hole Optimization.
DOI: 10.5220/0010618902320239
In *Proceedings of the 18th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2021)*, pages 232-239
ISBN: 978-989-758-522-7

Zakian's framework (Bada, 1985), gained popularity because it provided good solutions to complex control problems. Khaisongkram et al. (Khaisongkram et al., 2004) used Zakian's framework to design a controller for a binary distillation column under disturbances. Hirapongsananurak et al. used it to design a controller for doubly-fed induction generator DFIG-based wind power generation (Chirapongsananurak et al., 2010). Interval constraint satisfaction was also used to design a robust fractional-order multivariable controller (Patil et al., 2017). Researchers extended Zakian's approach to controller design with fuzzy constraints. Tuan et al. (Tyan et al., 1996) proposed a methodology of fuzzy constraint-based controller design via constraint-network processing. Guan et al. (Guan & Friedrich, 1993) used a fuzzy CSP in structural design.

The reliance on numerical solutions of inequalities limited the applicability of the method of inequalities. The applicability of the approach can be extended by the use of new and powerful artificial intelligence methodologies. To our knowledge, there has been little work on the use of artificial intelligence to solve a CSP for control system design with crisp constraints. The solution of these problems for complex systems is quite difficult and warrants the use of intelligent methodologies such as deep learning and evolutionary algorithms. Deep learning algorithms provide an excellent tool for precisely tuning controllers due to their flexible representation of decision variables and performance evaluation, as well as their robustness to difficult search environments (Ding-gang et al., 2020). Applications of evolutionary algorithms include parameter and structure optimization for controller design and model identification (Haralampidis et al., 2005), fault detection (Omer et al., 2016), robustness analysis (Fleming & Purshouse, 2002). This paper proposes the use of Modified Black Hole algorithm (MBH) and Convolutional Neural Networks to design controllers solving a CSP. The constraints are selected to provide values for control design criteria that guarantee good controller performance.

To demonstrate the CSP control design methodologies, two design examples are presented. The first is the design of a PID controller for an armature controlled DC motor. This simple example, while solvable by traditional approaches, serves to clearly explain the controller design steps. The second example is the well-known Bouc-Wen hysteresis model. Hysteretic behaviour occurs in a vast range of physical systems such as magnetism, piezo-electric materials, and mechanical vibration (Din et al., 2016). However, conventional controller design is difficult for the Bouc-Wen model because it is highly nonlinear and includes a large number of parameters, making its model identification a challenging problem (Charalampakis & Koumousis, 2008). The second example includes comparison to two well known algorithms, particle swarm optimization (PSO) (Kennedy et al., 1995) and the firefly algorithm (Xin-She, 2008).

The paper is organized as follows. Section 2 reviews the constraint satisfaction problem and, Section 3 presents the penalty function method. Section 4 discusses the use of convolutional neural network to solve CSPs. Section 5 presents two examples and their simulation results. Section 6 is the conclusion.

2 CONSTRAINT SATISFACTION PROBLEM (CSP)

A CSP is defined in terms of a tuple (X, D, C), where $X = \{x_1, \ldots, x_n\}$ is a finite set of variables with domains $\{D_1, \ldots, D_n\}$, respectively, and C is a ranked finite set of constraints. Each constraint in C restricts the values that one can simultaneously assign to a subset of the variables. A constraint is defined as n-ary if it contains n variables. A binary constraint CSP is a CSP with unary and binary constraints only. The main goal of the CSP is to assign at least one value to each variable, while satisfying all the constraints in C. The following is a formal definition of the CSP(Popescu, 1997).

Definition 1: Constraint Satisfaction Problem.

Given a set of n variables $\{x_1, \ldots, x_n\}$ with domains $\{D_1, \ldots, D_n\}$, respectively and a set of constraints $\{C_1, \ldots, C_l\}$ find at least one set of values $\{v_1, \ldots, v_n\}$ that satisfy all the constraints.

Example: Consider the CSP with

(i) the set of variables:
$X = \{x_1, x_2, x_3, x_4\}$,
(ii) the domains:

$D_{x1} = \{0,1,2,3\}$; $D_{X2} = \{1,3\}$; $D_{X3} = \{1,3,4,5\}$;

and (iii) the constraints:

$C = \{x_1 < x_2; x_1 + x_3 < x_2; x_2 + x_3 > 3; x_1 + x_2 > x_3\}$,

an admissible instantiation is $x_1 = 0, x_2 = 3, x_3 = 1$.

3 MBH SOLUTION USING A PENALTY FUNCTION

A constrained optimization problem can be converted into an unconstrained problem and solved using an evolutionary algorithm. The solution is obtained using penalty methods by adding (or multiplying) a violation term to the cost function that introduces a high cost for constraint violation. Consider the constrained optimization problem:

$$Minimize\ \{f(x): x\ \in C\} \tag{1}$$

where f is function on $\mathcal{R}^n$ and C is a constraint set in $\mathcal{R}^n$, or

$$Minimize\ \{f(x)\}, \quad s.t. \quad g(x) \geq g_0 \tag{2}$$

The penalty function method replaces problem (2) with an unconstrained approximation of the form:

$$Minimize\ \left\{f(x) + \sum_i w_{gi} V_{gi}\right\} \tag{3}$$

where w_{gi} is the i^{th} weight and V_{gi} is a penalty function on $\mathcal{R}^n$.Alternatively, the penalty function is implemented as follows:

$$Minimize\ \{f(x)\left(1 + \sum_i w_{gi} V_{gi}\right)\} \tag{4}$$

The penalty function V is defined as:

$$V\{g(x) \geq g_0\} = \begin{cases} 0, & g(x) \geq g_0 \\ 1 - \dfrac{g(x)}{g_0}, & g(x) < g_0 \end{cases} \tag{5}$$

or

$$V\{g(x) \leq g_0\} = \begin{cases} 0, & g(x) \leq g_0 \\ \dfrac{g(x)}{g_0} - 1, & g(x) > g_0 \end{cases} \tag{6}$$

The modified black hole algorithm, which is discussed in the next section, is used to minimize the penalty value (5).

3.1 Modified Black Hole Algorithm

The Black Hole (BH) algorithm is an optimization technique inspired by the engulfing behavior of black holes(Gan & Zhang, 2019). The method was shown to improve the convergence rate and efficiency of the particle swarm optimization (PSO) algorithm (Gan & Zhang, 2019). A modified version of the black hole algorithm (MBH) overcomes drawbacks of the BH algorithm, such as getting trapped in local minima, and can solve both high and low dimensional problems (Yaghoobi & Mojallali, 2016).

Like other population-based evolutionary algorithms, the MBH generates a random population and calculates the cost function values for all the particles. The particle with the lowest cost is designated as the black hole and all other particles are designated as stars. At this step, stars begin to gravitate towards the black hole and their movement can be formulated as:

$$x_{star}^{i+1} = x_{star}^{i} + C \times d \tag{7}$$

where x_{star}^{i+1} and x_{star}^{i} are the star locations in their respective generations. C is a matrix whose elements are uniformly distributed random numbers, ranging between 0 and 2, and d is the vector of connectivity between each particle and the black hole. Fig. 1 shows how a star moves towards the black hole.

After each iteration, each star becomes closer to the black hole and its cost is recalculated. If the cost of a particle becomes lower than that of the black hole, they exchange locations, as shown in Fig. 2. If a particle approaches the minimum distance from the black hole while providing a higher cost, it is removed and a new particle is generated randomly in the search space. The distance is defined as:

$$r = \left(\frac{f_c}{\sum_{i=1}^{N_{pop}} f_n}\right)^2 \tag{8}$$

where f_c stands for the cost of black hole, N_{pop} is the number of members in each iteration, and f_n is the n^{th} particle cost. At the end of every generation, the black hole will always occupy the location that provides the lowest cost and the stars are propelled towards the best search space.

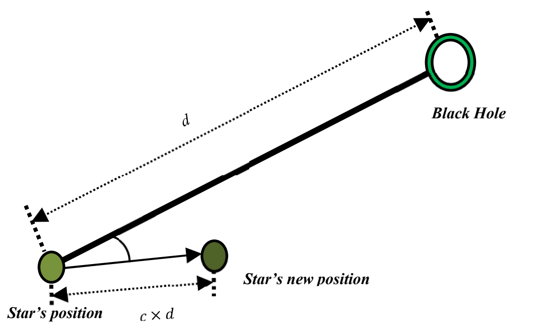


Figure 1: Moving particles (stars) towards the black hole.

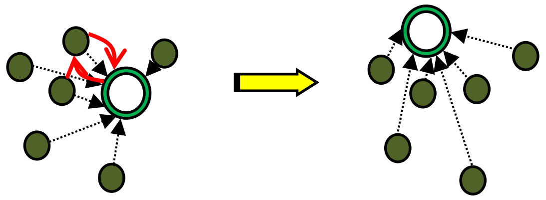


Figure 2: Exchanging position of a star and black hole.

3.2 Convergence Analysis of MBH

A critical issue with metaheuristic algorithms is their convergence to an optimal, or at least satisfactory, solution. Powerful hybrids that combine metaheuristic techniques with well-established methods from mathematical programming give the convergence issue a new relevance (Gutjahr, 2009). Every evolutionary optimization algorithm such as MBH includes the following steps:

1. Find $x_0 \in S$ and set $t = 0$.
2. Generate a vector $V_t \in \mathcal{R}^n$ using a probability measure μ_t.
3. Set $x_{t+1} = D(x_t, V_t)$, choose μ_{t+1}, set $t = t + 1$ and return to Step 2.

where D is a mapping that combines the new velocity vector, V_t, with the current solution, x_t.

Any metaheuristic optimization algorithm will at least converge to a local minimum if the algorithm satisfies the *algorithm condition* and the *convergence condition* (Van den Berg & Engelbrecht, 2010). The two conditions are:

Condition I (Algorithm Condition): The mapping $D: S \times \mathcal{R}^n \to S$ must satisfy $f(D(x_t, V_t)) \le f(x_t)$. This condition simply says that the solution generated by mapping D in iteration $t + 1$ is no worse than the solution in iteration t.

Condition II (Convergence Condition): For any subset $A \subseteq S$ with $c(A) > 0$, we have that:

$$\prod_{t=0}^{\infty} \left[1 - \mu_t(A)\right] = 0 \tag{9}$$

Condition II means that for any measurable $A \subseteq S$ with non-negative measure c, the probability of repeatedly missing the set A, must be zero. Conditions I and II lead to the following theorem.

Theorem 1 (Solis & Wets, 1981)**:** Suppose that f is a measurable function, S is a measurable subset of $\mathcal{R}^n$ and Condition I and Condition II are satisfied. Let $\{x_t\}_{t=0}^{\infty}$ be a sequence generated by a random search algorithm. Then x_t converges almost surely to the *optimality region* R_ϵ

$$\lim_{t\to\infty} P[x_t \in R_\epsilon] = 1 \tag{10}$$

where $P[x^t \in R_\epsilon]$ is the probability that the point x_t generated by the algorithm at time t is in R_ϵ.

Proof: Considering Condition I, if $x_t \in R_\epsilon$ then $x_{t'} \in R_\epsilon$ for all $t' \ge t + 1$. Thus, the probabilities satisfy

$$P[x^t \in R_\epsilon] = 1 - P[x^t \in S \backslash R_\epsilon] \ge 1 - \prod_{l=0}^{t}[1 - \mu_l(R_\epsilon)] \tag{11}$$

Combining (11) and Condition II gives

$$1 \ge \lim_{t\to\infty} P[x^t \in R_\epsilon] \ge 1 - \lim_{t\to\infty} \prod_{l=0}^{t-1}[1 - \mu_l(R_\epsilon)] = 1 \tag{12}$$

Corollary I: The MBH converges almost surely to the optimality region R_ϵ.

Proof: It was shown in (Yaghoobi & Mojallali, 2016) that the position of the black hole does not change until a better solution is found. Hence, the MBH satisfies Condition I. Since MBH omits the stars that reach the minimum distance defined by equation (11) and new stars are generated randomly in the search space, the sample space from which any new star is drawn has the support $M_t = S$. This implies that $c[M_t] = c[S]$, which implies that Condition II is satisfied. It follows from Theorem 1 that the MBH converges almost surely to the optimality region. Corollary I establishes that the MBH is a global search algorithm.

4 CONVOLUTIONAL NEURAL NETWORK FOR SOLVING CSP

With the expansion of interest in artificial intelligence (AI) applications, their usage in solving mathematical problems has grown exponentially. There have been many attempts to apply these AI techniques to constraint satisfaction problems. Here a constraint logic program (CLP) is treated as a network of constraints to solve the constraint satisfaction problem. Each computation in a CLP can be shown as a sequence of linear steps, since the check satisfiability of the system of constraints is applied at each resolution step, which is linear in the size of the current constraint problem. The constraint propagation information is performed at each step during any CLP derivation. To our knowledge, none of the recent advances in deep learning have been exploited to solve this important problem. We can represent a CSP with an artificial neural network where the variables of the problem are represented by a finite number of neurons divided into multiple layers. The ANN model of a CSP is shown in Fig. 3, where the ANN is a mapping of a set of input patterns I_{ij} to a corresponding set of output patterns $O_{i+1,k}$. The training data is a set of ordered pairs $H_{ij} = \{I_{ij}, O_{i+1,k}\}$ that is used to train the network. The training process consists in the computation of the set of values $\{v_1, \ldots, v_n\}$ that satisfies the constraints $\{C_1, \ldots, C_l\}$.

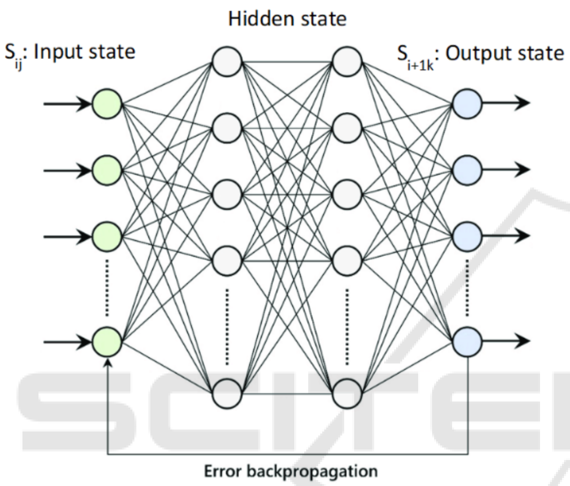


Figure 3: The ANN model of a CSP.

5 DESIGN EXAMPLES

We apply the design methodologies to two systems, an armature-controlled DC motor and a nonlinear Bouc-Wen system. The first example is intended to show the steps of the design methodologies while the second demonstrates the ability of the methodologies to handle difficult controller design problems. We design PID controller for each of the two systems. The controller generates a control signal using the error signal, its integral and its derivative:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{d}{dt} e(t) \tag{13}$$

where $u(t)$ is the control signal, $e(t)$ is the error signal defined as $e(t) = R(t) - y(t)$, the difference between the reference signal $R(t)$ and the output signal $y(t)$. The controller parameter, K_p, K_i, and K_d, denote the proportional gain, the integral gain, and the derivative gain, respectively.

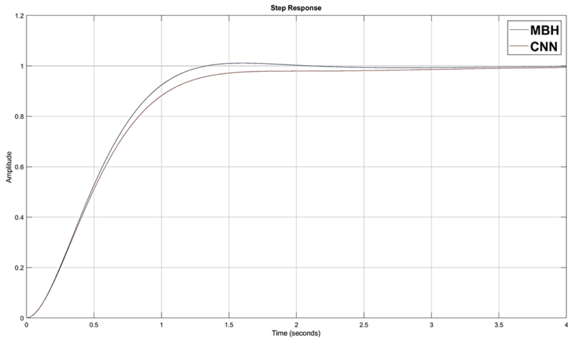


Figure 4: Unit Step response comparison between MBH and CNN.

Example 1. Linear System (DC Motor).

Consider an armature-controlled DC motor whose transfer function with armature voltage as input and angular position as output is:

$$G(s) = \frac{1}{S^3 + 9S^2 + 22s + 15} \tag{14}$$

The controller is designed to satisfy the following design constraints:

Table 1: Step response evaluation criteria for the DC motor.

	Violation	Cost	Settling Time	Peak Value	Final Value
Max.	0.0138	1.8555	1.8549	1.0638	1.0013
Min.	0	0.9996	0.9996	1.0135	0.9999
Mean	6.9416×10^{-4}	1.2041	1.1967	1.0231	1.00006
Std.	0.0031	0.2503	0.2539	0.0124	3.1102×10^{-4}

$$0.9 < Maximum\ Overshoot < 1.1 \tag{15}$$

$$Steady - state\ Error < \pm 5\% \tag{16}$$

The cost function for MBH algorithm is the integral of the error over time. Twenty runs of MBH algorithm and deep neural network with a weight vector $w_g = [1 \quad 1000 \quad 100]$, yield controllers that provide step responses that satisfy the design constraints, as shown in Fig. 2. The best run provided the controller parameter values $K_p = 38.2401, K_i = 28.52$ and $K_d = 10$ for the CNN method and $K_p = 37.9147, K_i = 28.7847$ and $K_d = 10$ for the MBH method. Table 1 shows the values of the design criteria for the selected parameter values. The simulation results clearly show that the proposed approach provides a good design for the DC motor with a fast response, small overshoot and negligible steady-state error. Fig. 4 shows the step response comparison between two different proposed methods. As it is clear from the figure, The MBH-Based method has a faster response with a small and almost negligible overshoot.

Example 2. Nonlinear Bouc-Wen System.

The Bouc–Wen model was originally applied for nonlinear vibrational mechanics (Xin-She, 2008). The model represents hysteresis as the superposition of a linear component $X(t)$ and a hysteretic component $h(t)$. The classical hysteretic Bouc–Wen model is described as follows:

$$y(t) = X(t) + h(t) = k.u(t) + h(t) \tag{17}$$

$$\dot{h}(t) = \alpha\dot{u}(t) - \beta\dot{u}(t)|h(t)|^{n} - \gamma|\dot{u}(t)||h(t)|^{n-1}h(t) \tag{18}$$

where $u(t)$ is the input, $y(t)$ is the output, and k, α, β, γ and n are the model parameters that determine the shape of the hysteresis curves. The parameter n is often equal to unity to simplify the model and the hysteresis component then becomes:

$$\dot{h}(t) = \alpha\dot{u}(t) - \beta\dot{u}(t)|h(t)| - \gamma|\dot{u}(t)|h(t) \tag{19}$$

We consider a Bouc-Wen model with parameter values $k = 0.2181, \alpha = -0.1453$, $\beta = 2.8847$ and $\gamma = 3.4124$ (Gan & Zhang, 2019), with the input signal $u(t) = 5\sin(2\pi \times 40t) + 5$. The model is used to generate the data using by the deep neural network to select the controller parameters. Fig. 5 shows the Simulink implementation of the Bouc-Wen model.

The controller must satisfy the following design constraints:

$$\text{I. Error Constraint: } Error < 10 \tag{20}$$

Table 2: Response characteristics for the Bouc-Wen system.

	Error	Slope
MBH	9.4035	0.9993
CNN	9.6452	0.9975
PSO	27.6085	0.8694
FA	32.6452	0.9108

II. Input-output Constraint:

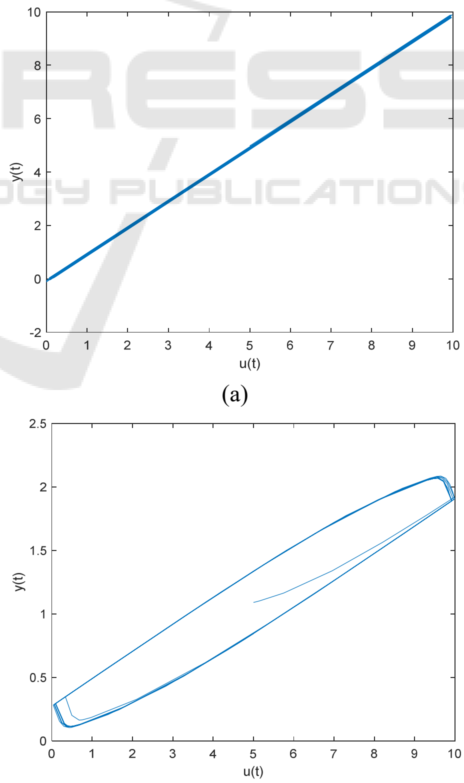
$$0.95 \leq slope\ of\ input - output\ diagram \leq 1.05 \tag{21}$$

where $Error$ is defined as the integral square error:

$$Error = \int (y(t) - u(t))^2 dt \tag{22}$$

The proposed CNN approach selected the PID controller parameter values $K_p = 92.8537, K_i = 49.3467$, and $K_d = 7.1$, with an integral square error of 9.2457. The MBH penalty-based method selected the values $K_p = 99.4486, K_i = 61.1953$, and $K_d = 11.1$. The integral square error for this design is 9.4035. Both methods provide a feasible integral square error that is lower than the upper bound of 10.

The input-output plot of Fig. 5 shows that the controlled system follows the output in both the controlled and uncontrolled scenarios. The input-output plot is linear with slope 0.993, which satisfies the desired criteria. The tracking performance improves with the MBH and CNN-tuned PID controllers. Table 2 is a comparison between our two controllers, PSO (Kennedy et al., 1995), and the Firefly Algorithm (Xin-She, 2008). Fig. 6 demonstrates the error evolution over time for the four approaches. The figure shows that the error of the proposed design is always significantly smaller than the other approaches. The error for proposed design drops much faster than other approaches then remains within a much smaller bounded range. The results show that the MBH and CNN-based approaches provide more accurate tracking than PSO and FA.



(a)

(b)

Figure 5: Input-Output plot of (a) controlled and (b) uncontrolled systems with the input $u(t) = 5\sin(2\pi * 40t) + 5$.

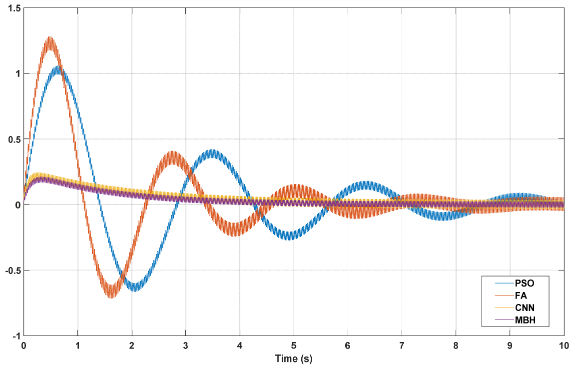


Figure 6: Error of four different studied designs over time.

6 CONCLUSION

This paper proposes intelligent control system design by solving a constraint satisfaction problem. The problem is solved using MBH optimization and using a deep neural network. To demonstrate the design methodology, two design and simulation examples are presented. The first example is PID control for an armature controlled DC motor and it demonstrates the simplicity of the design methodology. The second is PID control of Bouc-Wen hysteresis and it demonstrates the applicability of the methodology to challenging nonlinear systems. The performance of the Bouc-Wen controller obtained using the proposed method is compared to the results obtained using particle swarm optimization and the firefly algorithm. Simulation results show that the MBH and CNN solution provide better controller performance with faster and more accurate tracking that compares favorably with the particle swarm algorithm and the firefly algorithm. Future work will apply the methodology to nonlinear multivariable systems using input-output data without the benefit of a mathematical model.

REFERENCES

Tsang, E. (2014). Foundations of constraint satisfaction: the classic text. BoD–Books on Demand.

Lecoutre, C., Saïs, L., Tabary, S., & Vidal, V. (2009). Reasoning from last conflict (s) in constraint programming. Artificial Intelligence, 173(18), 1592-1614.

Alfa, A. S., Maharaj, B. T., Lall, S., & Pal, S. (2016). Mixed-integer programming based techniques for resource allocation in underlay cognitive radio networks: A survey. Journal of Communications and Networks, 18(5), 744-761.

Barrett, C., & Tinelli, C. (2018). Satisfiability modulo theories. In Handbook of Model Checking (pp. 305-343). Springer, Cham.

Lifschitz, V. (2019). Answer set programming (pp. 1-147). Berlin: Springer.

Ohrimenko, O., Stuckey, P. J., & Codish, M. (2007, September). Propagation= lazy clause generation. In International Conference on Principles and Practice of Constraint Programming (pp. 544-558). Springer, Berlin, Heidelberg.

Wu, H., & Van Beek, P. (2007, September). On universal restart strategies for backtracking search. In International Conference on Principles and Practice of Constraint Programming (pp. 681-695). Springer, Berlin, Heidelberg.

Bessiere, C. (2006). Constraint propagation. In Foundations of Artificial Intelligence (Vol. 2, pp. 29-83). Elsevier.

Dechter, R., & Rossi, F. (2006). Constraint satisfaction. Encyclopedia of Cognitive Science.

Ruttkay, Z. (1998). Constraint satisfaction-a survey. CWI Quarterly, 11(2&3), 123-162.

Zakian, V., & Al-Naib, U. (1973, November). Design of dynamical and control systems by the method of inequalities. In Proceedings of the Institution of Electrical Engineers (Vol. 120, No. 11, pp. 1421-1427). IET Digital Library.

Zakian, V. (1979, June). New formulation for the method of inequalities. In Proceedings of the Institution of Electrical Engineers (Vol. 126, No. 6, pp. 579-584). IET.

Zakian, V. (1996). Perspectives on the principle of matching and the method of inequalities. International Journal of Control, 65(1), 147-175.

Zakian, V. (2005). Control systems design. Springer-Verlag London Limited.

Zakian, V. (1991). Well matched systems. IMA Journal of Mathematical Control and Information, 8(1), 29-38.

Bada, A. T. (1985, November). Design of delayed control systems using Zakian's framework. In IEE Proceedings D-Control Theory and Applications (Vol. 132, No. 6, pp. 251-256). IET.

Khaisongkram, W., Banjerdpongchai, D., & Arunsawatwong, S. (2004, July). Controller design for a binary distillation column under disturbances with bounds on magnitudes and derivatives using Zakian's framework. In 2004 5th Asian Control Conference (IEEE Cat. No. 04EX904) (Vol. 3, pp. 1676-1684). IEEE.

Chirapongsananurak, P., Hoonchareon, N., & Arunsawatwong, S. (2010, November). Controller design for DFIG-based wind power generation using Zakian's framework. In TENCON 2010-2010 IEEE Region 10 Conference (pp. 1284-1289). IEEE.

Patil, M. D., Nataraj, P. S. V., & Vyawahare, V. A. (2017). Design of robust fractional-order controllers and prefilters for multivariable system using interval constraint satisfaction technique. International Journal of Dynamics and Control, 5(1), 145-158.

Tyan, C. Y., Wang, P. P., Bahler, D. R., & Rangaswamy, S. P. (1996). A new methodology of fuzzy constraint-based controller design via constraint-network

processing. IEEE transactions on fuzzy systems, 4(2), 166-178.
Guan, Q., & Friedrich, G. (1993, March). Fuzzy control over constraint satisfaction problem solving in structural design. In [Proceedings 1993] Second IEEE International Conference on Fuzzy Systems (pp. 1316-1320). IEEE.
Gao, D. G., Sun, Y. G., Luo, S. H., Lin, G. B., & Tong, L. S. (2020). Deep learning controller design of embedded control system for maglev train via deep belief network algorithm. Design Automation for Embedded Systems, 24(3), 161-181.
Haralampidis, Y., Papadimitriou, C., & Pavlidou, M. (2005). Multi-objective framework for structural model identification. Earthquake engineering & structural dynamics, 34(6), 665-685.
Omer, Z. M., Fardoun, A. A., & Hussain, A. (2016, July). Large scale photovoltaic array fault diagnosis for optimized solar cell parameters extracted by heuristic evolutionary algorithm. In 2016 Ieee Power And Energy Society General Meeting (pesgm) (pp. 1-5). IEEE.
Fleming, P. J., & Purshouse, R. C. (2002). Evolutionary algorithms in control systems engineering: a survey. Control engineering practice, 10(11), 1223-1241.
Ding, B., Li, Y., Xiao, X., & Tang, Y. (2016, December). Optimized PID tracking control for piezoelectric actuators based on the Bouc-Wen model. In 2016 IEEE International Conference on Robotics and Biomimetics (ROBIO) (pp. 1576-1581). IEEE.
Charalampakis, A. E., & Koumousis, V. K. (2008). Identification of Bouc–Wen hysteretic systems by a hybrid evolutionary algorithm. Journal of Sound and Vibration, 314(3-5), 571-585.
Kennedy, J., & Eberhart, R. (1995, November). Particle swarm optimization. In Proceedings of ICNN'95-international conference on neural networks (Vol. 4, pp. 1942-1948). IEEE.
Yang, X. S. (2009, October). Firefly algorithms for multimodal optimization. In International symposium on stochastic algorithms (pp. 169-178). Springer, Berlin, Heidelberg.
Gan, J., & Zhang, X. (2019). Nonlinear hysteresis modeling of piezoelectric actuators using a generalized Bouc–Wen model. Micromachines, 10(3), 183.
Yaghoobi, S., & Mojallali, H. (2016). Modified black hole algorithm with genetic operators. International Journal of Computational Intelligence Systems, 9(4), 652-665.
Gutjahr, W. J. (2009). Convergence analysis of metaheuristics. In Matheuristics (pp. 159-187). Springer, Boston, MA.
Van den Bergh, F., & Engelbrecht, A. P. (2010). A convergence proof for the particle swarm optimiser. Fundamenta Informaticae, 105(4), 341-374.
Solis, F. J., & Wets, R. J. B. (1981). Minimization by random search techniques. Mathematics of operations research, 6(1), 19-30.
Popescu, I. (1997). Using artificial neural networks for constraint satisfaction problem. Nonlinear Analysis: Theory, Methods & Applications, 30(5), 2937-2944.