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Design optimization of fuzzy controllers in building structures using the crystal structure algorithm (CryStAl)

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ABSTRACT

The current study uses a recently-developed metaheuristic method called Crystal Structure Algorithm (CryStAl) to achieve optimized vibration control in structural engineering. More specifically, this algorithm, which is inspired by the well-established crystallographic principles underlying the formation of crystalline solids in nature, is applied to the optimization of fuzzy logic controllers in building structures. To demonstrate the capability of this method in solving real engineering problems, two real-size building structures, one with three and the other with twenty stories, are considered. The fuzzy controllers are implemented through an active control system to control the seismically-induced vibrations of the structures intelligently. The evaluation criteria utilized to assess the overall performance of the optimization method applied to the fuzzy control system are presented and discussed. Through nonlinear structural analyses, the ductility, energy dissipation, and other nonlinear characteristics of the structures are also considered as the structural responses to be controlled. The computational results obtained from this novel metaheuristic algorithm are compared with those of the other expert systems from the optimization literature. The findings of this paper demonstrate that the Crystal Structure Algorithm is capable of outranking the other methods in the majority of considered cases.

1. Introduction

Human demand for the control of natural forces has always been of great importance and has led to many scientific and engineering advances throughout history. Automatic control systems are engineered devices that automatically, i.e., without any external assistance, make a series of checks at desired times and implement appropriate corrections if any discrepancies are found with respect to the anticipated results. Most of these methods resemble a thoughtful human being and perform a pre-determined series of tasks to achieve a predefined goal. In general, a major challenge in the design of engineering structures is the control of vibration amplitudes, which includes the limits of operation and safety. One of the modern approaches to vibration amplitude control is based on using structural control systems which are divided into two main categories: (1) passive, and (2) active/hybrid/semi-active control systems.

In recent decades, many researchers have used fuzzy logic to control the response of structures to earthquake stimulations, aiming to convert the equations of motion to analytical equations that can be solved algebraically. In this approach, in many cases, minimizing the objective function is on the agenda; while this approach does not result in absolute optimal controllers, it has been practically used for many applications. A fuzzy logic controller works based on fuzzy logic, in which, unlike classical logic, logical variables with continuous values in a specific range are used. The fuzzy control theory has attracted the attention of many researchers in the field of active and semi-active control. The main advantages of using fuzzy logic are its greater reliability and better nonlinear performance. Also, the calculations required in this method are relatively simple and can be implemented inside a fuzzy chip.

In this paper, the optimization of fuzzy logic controllers has been considered, where we investigate the applicability of metaheuristic algorithms to improving the performance of these intelligent systems. The Crystal Structure Algorithm (CryStAl), proposed by Talatahari, *et al.* [1], is utilized as the main optimization method. This algorithm is developed inspired by the structural design principles of crystalline solids, such as the existence of lattice and basis in their configurations [2]. Two 3-story

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and 20-story real-size building structures are utilized for numerical investigations. At the same time, fuzzy controllers are implemented through an active control system to intelligently control the seismically-induced vibration of the structures. By conducting nonlinear structural analyses, the ductility, energy dissipation, and other nonlinear characteristics of the structures are also considered as structural responses to be controlled. Knowing that the performance of such a recently-proposed metaheuristic algorithm should be evaluated in dealing with complex real-world problems, CryStAl is utilized as an intelligent technique for the fuzzy-based vibration control of building structures in this study for the first time.

2. Literature review

Optimization is the process of tuning a predefined set of variables in which the main goal is to provide the best levels for the targets concerning the specifications of the considered system. In recent decades, the optimum design of fuzzy systems has been of great interest because knowledge-based fuzzy controllers cannot provide acceptable and reliable solutions to complex real-life problems. Ochoa, *et al.* [2] investigated the optimum design of fuzzy controllers with an improved differential evolution (DE) algorithm considering dynamic parameter adaptation. The authors found that, in general, using Type-1 or Interval Type-2 fuzzy systems in DE is better than using the original technique, albeit this will depend highly on the specific problem being considered. Peraza, *et al.* [3] utilized the harmony search algorithm for the dynamic parameter adaptation of fuzzy logic controllers. In this research work, the findings of 30 tests for each technique revealed that stability can be achieved by using perturbations; the authors observed this when utilizing a generalized Type-2 fuzzy system for the controller with or without perturbation. Civelek [4] considered the optimization of blade pitch angle fuzzy controller with a genetic algorithm. Improved wind turbine pitch angle control was obtained using a Sugeno-Takagi controller designed by Advanced Intelligent Genetic Algorithm (AIGA), which according to the authors, would increase the output power stability of wind turbines, resulting in a significantly more stable power supply to the energy network. Radu-Emil, *et al.* [5] proposed cost-efficient fuzzy controllers for engineering applications through a slime mould algorithm (SMA). According to them, SMA was superior over the other metaheuristic algorithms that solve the identical optimization problem for optimum parameter tuning of cost-effective fuzzy controllers. David, *et al.* [6] presented a unique application of the Whale Optimization Algorithm (WOA) to solve a complicated control design and tuning problem involving fuzzy control systems that govern processes depicted as second-order servo systems with a variable parameter and integral component. In another study, David, *et al.* [7] proved that the WOA could be used to solve complex control problems in fuzzy control systems (FCSs) with reduced parametric sensitivity. Lagunes, *et al.* [8] presented fuzzy dynamic alpha parameter adjustment for generating a fuzzy controller with one input and one output with the goal of optimizing the fuzzy controller membership functions, which are optimized by a data vector created and evaluated using the Firefly Algorithm (FA). According to the authors, the findings of comparing type 1 and type 2 fuzzy logic systems were fairly comparable; thus, a noise would be added to the plants to examine their behavior during optimization. Xia, *et al.* [9] utilized inverted pendulum systems for the optimum design of fuzzy controllers based on dynamic parameter investigations, indicating the effectiveness of the proposed method using simulated results. Lotfy, *et al.* [10] proposed an improved version of the genetic algorithm for the optimum design of fuzzy controllers implemented in the speed control of DC motors. In contrast to existing fuzzy controllers, the authors concluded that the optimized fuzzy controller has accurate performance and fast convergence, and benefits from efficient hardware implementation. Ezzeddine [11] investigated the optimum design of fuzzy controllers using particle swarm optimization regarding the reactive power analysis combined with the frequency control scheme. These results indicated that the fuzzy logic controller (FLC) is effective in frequency stabilization and transient state improvement. Numerical simulations and experimental testing showed that this method may significantly enhance the transient state and, as a result, prevent the collapse of the self-excited induction generator (SEIG). Furthermore, Azizi, *et al.* [12] investigated the optimization of a fuzzy controller for a seismically excited nonlinear steel building, with objective functions and performance requirements taken into account concerning the nonlinear responses of the structure. In another study, Azizi, *et al.* [13] evaluated the effectiveness of an optimized fuzzy controller in decreasing the response of benchmark buildings with nonlinear behavior, using a hybrid optimization technique based on the ant lion optimizer (ALO) and Jaya algorithms, where 17 performance criteria were used to evaluate the performance of the improved controller using this technique. The numerical findings suggested that the reduction in building response (J_1 - J_3) for the 3- and 20-story benchmark structures were up to 23% and 21%, respectively. Azizi, *et al.* [14] evaluated the effectiveness of the improved fuzzy controller in decreasing the response of a 20-story benchmark building with nonlinear behavior. Azizi, *et al.* [15] employed Improved Charged System Search to optimize the fuzzy controller's membership functions and rule base. Talatahari and Azizi [16] proposed the Tribe-Charged System Search algorithm to optimize the membership functions and rule base of a fuzzy controller, in which the seismic inputs for nonlinear dynamic analysis were chosen and modified using an energy-based ground motion selection and modification approach for Tabriz. The suggested approach was compared to the conventional Charged System Search Algorithm and eight alternative metaheuristic algorithms in terms of performance. The authors asserted that the enhanced technique is able to achieve comparable outcomes in terms of decreasing building responses and damage caused by damaging earthquake records.

Given that many other researchers have studied the optimum design of fuzzy controllers, some of the most recent attempts are reviewed here. Mahmoodabadi and Javanbakht [17] investigated the optimum design of an adaptive fuzzy controller as an active suspension for a quarter-car model, in which the Gravitational Search Algorithm (GSA) was used to determine the optimal settings of the controller. The body acceleration and the relative displacement between the tire and the sprung mass were used in the optimization technique to define an appropriate objective function. Kayabekir, *et al.* [18] presented the optimum design of PID controlled active tuned mass damper via a modified harmony search. Moreover, Chaos Game Optimization (CGO), a newly proposed metaheuristic algorithm, was used to optimize the shape and size of truss systems [19]. Navabi, *et al.* [20] investigated the optimum fuzzy sliding mode control of fuel sloshing in a spacecraft using the PSO algorithm. Conker and Baltacioglu [21] presented a fuzzy self-adaptive PID control technique for driving HHO dry cell systems; the researchers stated that the self-adaptive fuzzy PID controllers outperformed the previously discussed conventional control approaches. For the performance improvement of the conventional approach, an improved version of the arithmetic optimization algorithm (IAOA) was presented to optimize fuzzy controllers used in steel structures with nonlinear behavior [22]. Zhang, *et al.* [23] proposed a novel robust optimum control algorithm and its application to semi-active controlled base-isolated structures; the simulation results confirmed the stability, robustness, and generalization capability of the proposed control algorithm. Rama Mohan Rao and Sivasubramanian [24] investigated the optimum design of fuzzy controllers utilizing self-configurable metaheuristic algorithms based on swarm intelligence. Azizi, *et al.* [25] proposed an enhanced version of the Upgraded Grey Wolf Optimizer (UGWO) to optimally design FLC membership functions and rule bases to minimize seismic structural damage. Marinaki, *et al.* [26] utilized a differential evolution algorithm for the optimal design of fuzzy controllers implemented in smart structures for vibrations suppression. Li and Yam [27] employed model-based fuzzy logic techniques for vibration control of complex systems. In addition, a complete review of the active structural vibration control

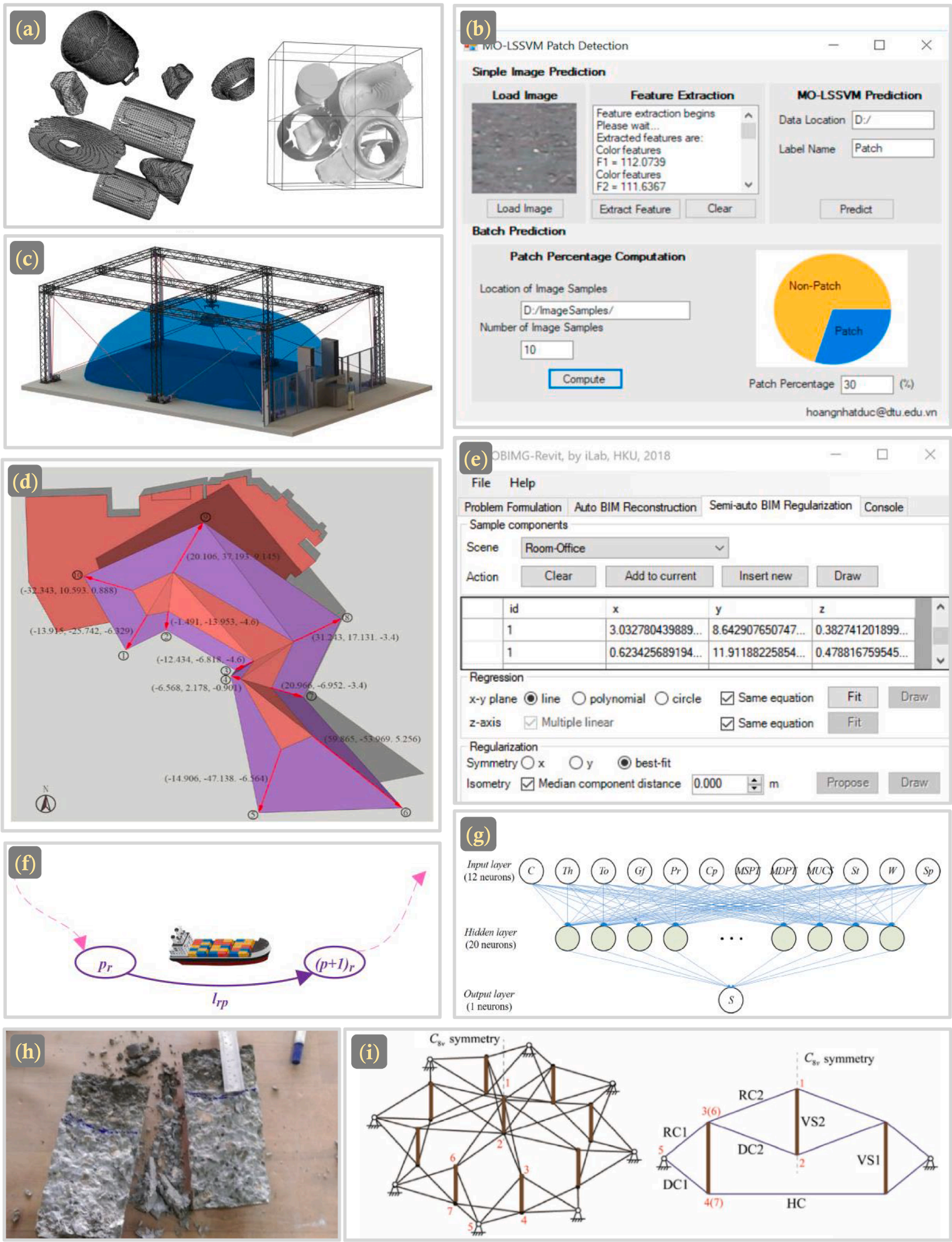

Fig. 1. (**a**) Metaheuristic-based packing of multiple objects into a rectangular cuboid package (Zhao, *et al.* [29]). (**b**) The graphical user interface of the metaheuristic optimized least squares support vector machine (MO-LSSVM) utilized for asphalt pavement patch detection (Hoang [30]). (**c**) Wrench-feasible workspace of a cable robot for automated masonry construction (Bruckmann and Boumann [31]). (**d**) Defining and controlling the depths of the eaves using the positions of multiple points in the 3D space for the design optimization of a complex building based on an artificial neural network (Si, *et al.* [33]). (**e**) The graphical interface of the COBIMG-Revit plugin for building information model optimization (Xue, *et al.* [34]). (**f**) Tactical-level planning in liner shipping (Pasha, *et al.* [35]). (**g**) The architecture of ELM-based ground response prediction model for predicting tunneling-induced ground responses (Zhang, *et al.* [36]). (**g**) Measurement of permeability of concrete containing metaheuristically optimized nano-MgO additive (Yazdchi, *et al.* [37]). (**i**) 3D and section views of a Levy cable dome structure (Chen, *et al.* [56]).

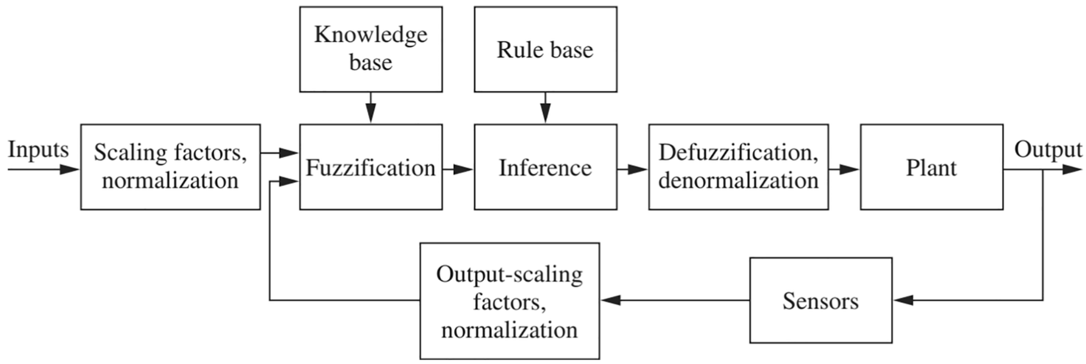

Fig. 2. A fuzzy logic controller implemented in a closed-loop control system.

and applications of different control schemes, including the fuzzy logic controllers, were presented by Korkmaz [28].

Regarding the fact that utilizing metaheuristics in different fields has been growing in recent years, some of the recent works are also summarized accordingly. Zhao, *et al.* [29] investigated the optimum design of 3D irregular object packing from 3D scans utilizing multiple metaheuristics (Fig. 1(a)). For design purposes, a novel methodology was presented in this research work, which starts with capturing each object's initial 3D shape data, followed by a metaheuristic-based packing optimization algorithm. In contrast, the proposed methodology was demonstrated to be effective in two situations with known optimum solutions and a third situation involving the packing of real-life as-is objects. Hoang [30] proposed a metaheuristic-based approach for image processing-based automatic recognition of asphalt pavement patches (Fig. 1(b)). In this paper, a data set of 1000 image samples was utilized for training and verifying the proposed integration of image texture analysis techniques while the experimental results demonstrated that the proposed model could achieve a good prediction result with a Classification Accuracy Rate = 95.30%, Positive Predictive Value = 0.96, and the Negative Predictive Value = 0.95. Bruckmann and Boumann [31] discussed the optimum design of automated masonry construction using cable robots with precise utilization of metaheuristic algorithms (Fig. 1(c)). In their study, the trajectory modeling was formulated employing cost functions derived from physical models of the cable robot by including the analysis of simulation results that illustrated the generated trajectories. Hu, *et al.* [32] conducted a critical review on automation and optimization in crane lift planning through metaheuristic algorithms. In this research work, the assessment of the crane lift planning automation and optimization was conducted. Furthermore, they presented an overview of the literature in crane lift planning, including the planning decision and the type of cranes, while the assumptions, objectives, decision variables, and constraints for each case were presented in detail. Si, *et al.* [33] developed a multi-objective optimization algorithm for the optimal design of complex buildings by combining an artificial neural network with performance evaluation of algorithms (Fig. 1(d)). In this study, multiple design variables, including the shape of the building's eaves, were optimized to improve building energy efficiency and indoor thermal comfort, while a surrogate model developed by an artificial neural network was used rather than a detailed simulation model to decrease the computing time. Xue, *et al.* [34] discussed the multimodal optimization and architectural design of building information modeling reconstruction from 3D point clouds (Fig. 1(e)). They investigated the reconstruction of repetitive objects as a multimodal optimization problem for registering the components of the building information model which had precise geometries and enriched semantics, while the topological information about repetition and symmetry in the reconstructed building information model was recognized and regularized for enriching the semantic aspects. Pasha, *et al.* [35] developed an integrated optimization method for tactical-level planning in liner shipping with heterogeneous ship fleet and environmental considerations (Fig. 1(f)). In this work, a decomposition-based optimization algorithm was proposed to solve the engineering model while the efficiency of the process was tackled by considering large-size problems. Zhang, *et al.* [36] developed a reinforcement learning-based optimizer utilizing metaheuristic algorithms for the improvement of predicting tunneling-induced ground responses (Fig. 1(g)). The results of this novel optimizer outperformed those of conventional metaheuristic optimization algorithms by their higher accuracy and lower computational cost. Yazdchi, *et al.* [37] used the Charged System Search (CSS) metaheuristic algorithm to optimize the amount of additive MgO nanoparticles in the composition of freeze–thaw resistant concrete, where they measured the compressive and tensile strengths as well as the permeability of concrete samples containing nanoparticles and compared them with those of ordinary concrete samples (Fig. 1(h)). Chen *et al.* [38] proposed a form-finding technique for prestressable pin-jointed structures by combining symmetry-based qualitative analysis with the Particle Swarm Optimization (PSO) (Fig. 1(i)). They also developed a PSO-based algorithm [39] for the intelligent design of non-trivial origami structures which were demonstrated to be computationally challenging using conventional techniques [40–42].

Shape annealing, a computational design process for structural design, has been used to create conventional and unique three-dimensional domes that meet the design criteria of efficiency, economy, usefulness, and aesthetics. Shape annealing, a stochastic structural optimization approach, employs lateral exploration to develop many designs of comparable quality that build a structural language of solutions, in contrast to deterministic structural optimization methods [38]. The simulated annealing method is used to determine if a randomly chosen shape rule should be implemented at a particular configuration stage in shape annealing (i.e., intermediate shape). A rule that is applicable to a current configuration state is chosen and applied to that state [43]. Once it is concluded that the new design does not break any constraints, it is submitted to the Metropolis algorithm, which uses the temperature profile to decide whether or not it should be accepted [44]. Nonetheless, the drawbacks of the mentioned method are threefold [45]: (i) The algorithm uses a gradient-based technique for form optimization; local optima may be obtained with nonconvex constraints; and the algorithm is unable to avoid obstacles. (ii) Since each step is followed by thorough shape optimization, a significant amount of computing effort is expended on manifestly unworthy topologies; and (iii) The application of a shape rule from the grammar does not always result in significant design modifications. Meanwhile, several research studies have been recently conducted in the area of intelligent vibration control of buildings; some notable examples include: (1) Using fluid viscous dampers for increasing the energy dissipation demand in multistory buildings by Zhou, *et al.* [46]; (2) parameter tuning investigation of tuned mass dampers for the seismic suppression of engineering structures by Prakash and Jangid [47], and (3) determining the seismic vulnerability of structural systems with nonlinear behavior by Elias and Matsagar [48].

```
procedure Crystal Structure Algorithm (CryStAl)
        Create random values for initial positions (x_i^j) of initial
crystals (Cr_i)
        Evaluate fitness values for each crystal
        while (t < maximum number of iterations)
            for i=1: number of initial crystals
                Create Cr_main
                Create new crystals by Eq. 4
                Create Cr_b
                Create new crystals by Eq. 5
                Create F_c
                Create new crystals by Eq. 6
                Create new crystals by Eq. 7
                    if new crystals violate boundary conditions
                        Control the position constraints for new crystals and
amend them
                    end if
                Evaluate the fitness values for new crystals
                Update Global Best (GB) if a better solution is found
            end for
            t=t+1
        end while
        Return GB
end procedure
```

Fig. 3. The pseudo-code of the Crystal Structure Algorithm (CryStAl) [1].

3. Fuzzy logic controller (FLC)

The main idea of control is to steer a system arbitrarily by monitoring the performance and adjusting the input of that system so that the performance of the system has to follow the desired actions. For this purpose, the output or state of the system is measured and fed to the controller. Based on this information, the controller decides how to change the system input to improve system performance. Many common control methods are model-based, meaning that the controller design is based on a mathematical model of the system. Linear mode feedback controllers and proportional-integral-derivative controllers are in this category. However, these methods are not always successful because an exact mathematical model of the system is unavailable in some cases. In such cases, if there is sufficient knowledge of how an expert controls the system, a fuzzy system can be designed to effectively control the system even if the mathematical model is completely unknown. In fact, one of the main applications of fuzzy systems in closed-loop control is nonlinear systems whose mathematical models are unknown or little is known about them. The diagram of a fuzzy controller is shown in general and schematically in Fig. 2. The steps of the control process with fuzzy controllers are as follows:

i. Determining the input and output variables of the controlled dynamic system (*Scaling*).
ii. Determining variables' upper and lower boundaries and creating fuzzy sets based on natural language parameters (*Normalization*).
iii. Create membership functions based on natural language variables (*Knowledge base*).
iv. Determining the relationships between the input and output of the control system and creating a fuzzy rule database (*Rule base*).
v. Determining the scale factor for system input and output in order to normalize them (*Output normalization*).
vi. Fuzzification of the control system inputs (*Fuzzification*).
vii. Forming a fuzzy inference engine and performing the inference process based on existing methods (*Inference*).
viii. Defuzzification of the control system outputs (*Defuzzification & Denormalization*).

4. Crystal structure algorithm (CryStAl)

The inspirational concept of CryStAl is based on the crystalline structures of natural solid minerals in which molecules, atoms, or ions are neatly arranged in three spatial directions. This algorithm was recently introduced by Talatahari, *et al.* [1], followed by further development and verifications [49,50]. Here, after a brief review of the foundations of this method, we will apply it to the problem considered in this paper.

According to the fundamentals of crystallography, crystals are made of a primary component known as 'lattice' which represents a periodic array of imaginary points in a predefined space. Besides, the specific arrangement of atoms in the structure of a crystal is known as 'basis' (for more details, see e.g. [51–53]). Therefore, crystals are determined by the combinations of these two components, i.e., *Crystal* $=$ *Lattice* $+$ *Basis*. To mathematically present CryStAl as a metaheuristic optimization algorithm, the Bravais model [54] is considered in which a periodic crystal structure is defined by a lattice geometry where any lattice point is

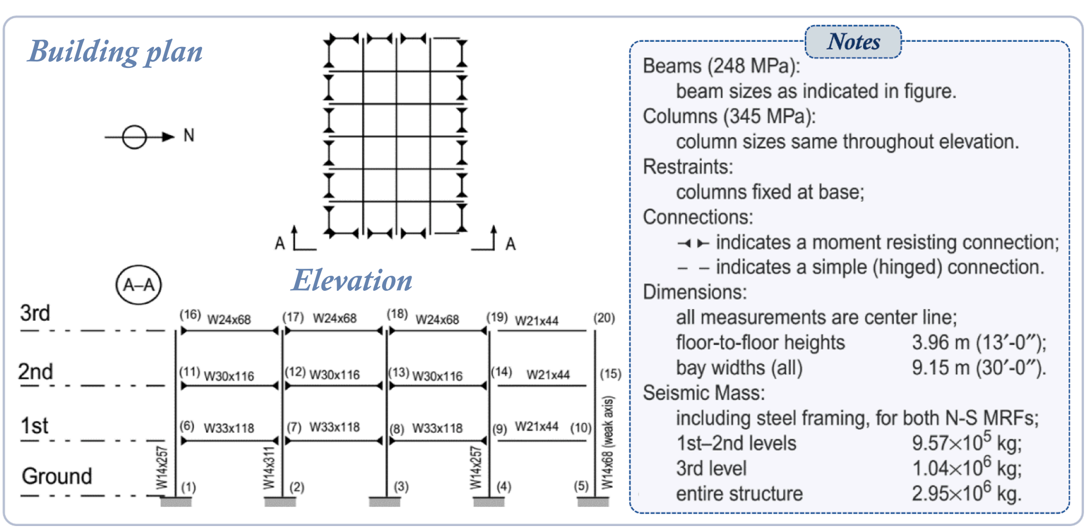

Fig. 4. Benchmark design example with three stories (adapted from [55]).

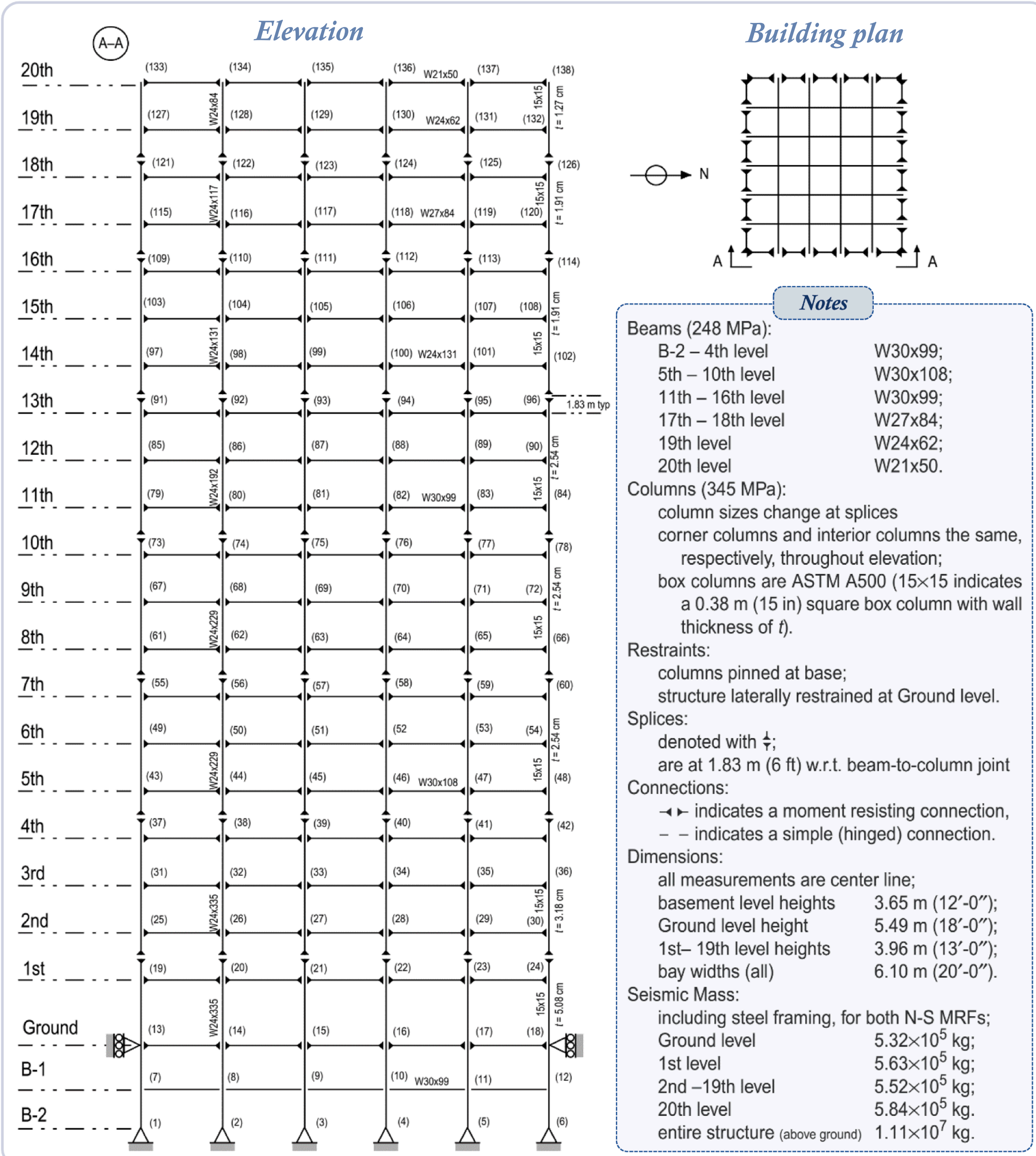

Fig. 5. Benchmark design example with 20 stories (adapted from [55]).

described by a vector as follows:

$$r = \sum n_i a_i, \tag{1}$$

where n_i is an integer, a_i is the shortest vector along the principal crystallographic directions, and i is the number of crystal corners. In CryStAl, each candidate solution of the optimization algorithm is considered as a single crystal in the space while the number of crystals is determined randomly for initialization purposes as follows:

$$Cr = \begin{bmatrix} Cr_1 \\ Cr_2 \\ \vdots \\ Cr_i \\ \vdots \\ Cr_n \end{bmatrix} = \begin{bmatrix} x_1^1 & x_1^2 & \cdots & x_1^j & \cdots & x_1^d \\ x_2^1 & x_2^2 & \cdots & x_2^j & \cdots & x_2^d \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_i^1 & x_i^2 & \cdots & x_i^j & \cdots & x_i^d \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ x_n^1 & x_n^2 & \cdots & x_n^j & \cdots & x_n^d \end{bmatrix}, \begin{cases} i = 1, 2, \cdots, n. \\ j = 1, 2, \cdots, d. \end{cases} \tag{2}$$

where n is the number of crystals (candidate solutions), and d is the dimension of the problem. The initial positions of these crystals are determined randomly in the search space by the following equation:

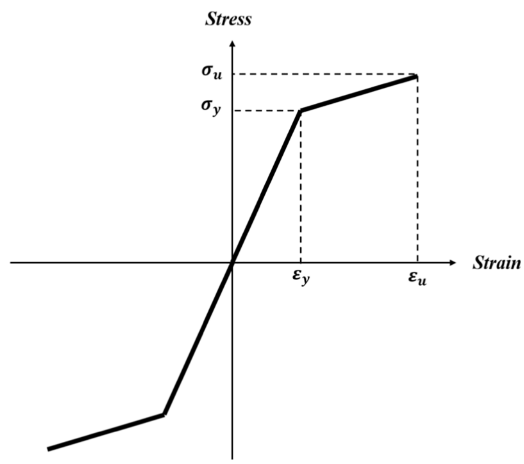

Fig. 6. Bilinear hysteresis model for structural members.

Table 1
Parameter summary of the nonlinear hysteresis model.

Properties	Value	Unit
Modulus of Elasticity (E)	200,000	MPa
Yield Strength of Columns (σ_y)	345	MPa
Tensile Strength of Columns (σ_u)	450	MPa
Yield Strength of Beams (σ_y)	248	MPa
Tensile Strength of Beams (σ_u)	400	MPa
Yield Strain (ε_y)	0.001725	mm/mm
Tensile Stain (ε_u)	0.18	mm/mm

$$x_i^j(0) = x_{i,min}^j + rand.(x_{i,max}^j - x_{i,min}^j), \begin{cases} i = 1, 2, \cdots, n. \\ j = 1, 2, \cdots, d. \end{cases} \tag{3}$$

where, $x_i^j(0)$ determines the initial position of the crystals; $x_{i,min}^j$ and $x_{i,max}^j$ are the minimum and maximum allowable values for the j-th decision variable of the i-th solution candidate; *rand* is a random number in the interval of [0,1]. Based on the concept of basis, each of the crystals at the corners is considered as the main crystal (Cr_{Main}) which is determined randomly by considering the initially created crystals (candidate solutions). The crystal with the best configuration is determined as Cr_b while the mean values of randomly selected crystals are determined as F_C. For updating the position of solution candidates in the search space, the basic principles of lattice are determined in which four kinds of updating process are determined as follows:

- *Simple cubicle*:

$$Cr_{New} = Cr_{Old} + rCr_{Main}, \tag{4}$$

where Cr_{New} is the new position, Cr_{Old} is the old position and r is a random number.

- *Cubicle with best crystals*:

$$Cr_{New} = Cr_{Old} + r_1Cr_{Main} + r_2Cr_b, \tag{5}$$

where Cr_{New} is the new position, Cr_{Old} is the old position, and r_1 and r_2 are random numbers.

- *Cubicle with mean crystals*:

$$Cr_{New} = Cr_{Old} + r_1Cr_{Main} + r_2F_c, \tag{6}$$

where Cr_{New} is the new position, Cr_{Old} is the old position, and r_1 and r_2 are random numbers.

- *Cubicle with best and mean crystals*:

$$Cr_{New} = Cr_{Old} + r_1Cr_{Main} + r_2Cr_b + r_3F_c, \tag{7}$$

where Cr_{New} is the new position, Cr_{Old} is the old position, and r_1 to r_3 are random numbers.

In order to deal with the solution variables x_i^j violating the boundary conditions of the variables, a mathematical flag is defined in which for the x_i^j outside the variables range, the flag orders a boundary change for the violating variables. The terminating criterion is considered based on the maximum number of iterations in which the optimization process is terminated after a fixed number of iterations. The pseudo-code of the algorithm is presented in Fig. 3.

By considering the fact that 'shape annealing' is a variant of the stochastic optimization approach 'simulated annealing' that uses shape grammars to specify allowed item orientations in various situations [43], the capability of this concept in enhancing the overall performance of metaheuristics is one of the other options that can be explored as a

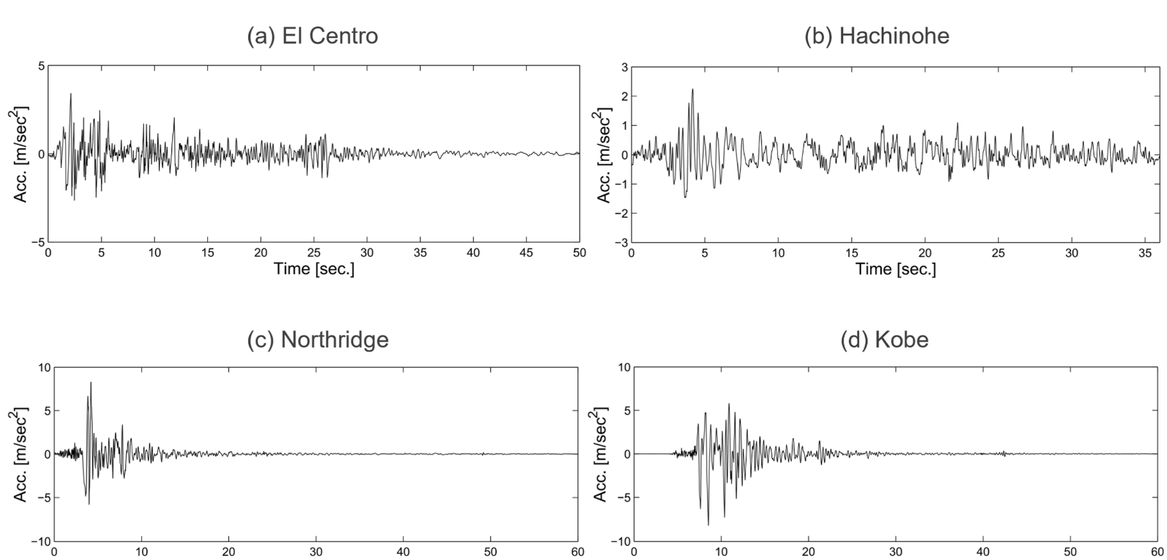

Fig. 7. Acceleration time histories of the considered earthquakes (adapted from [55]).

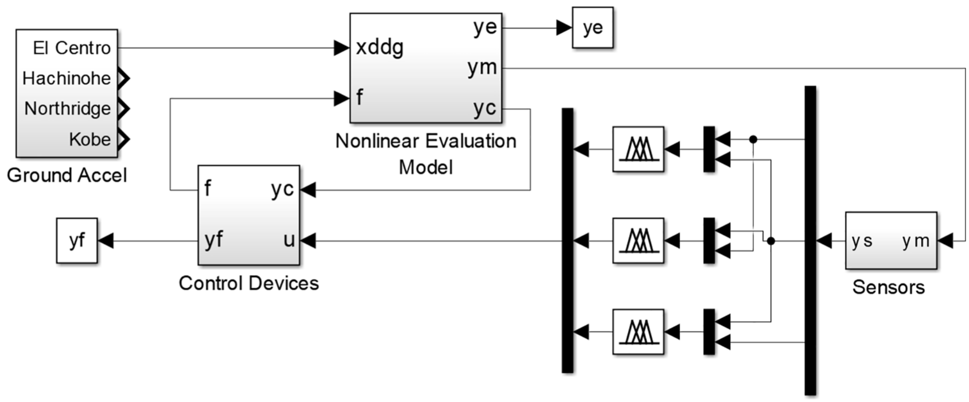

Fig. 8. Control scheme for the vibration control of the 3-story building.

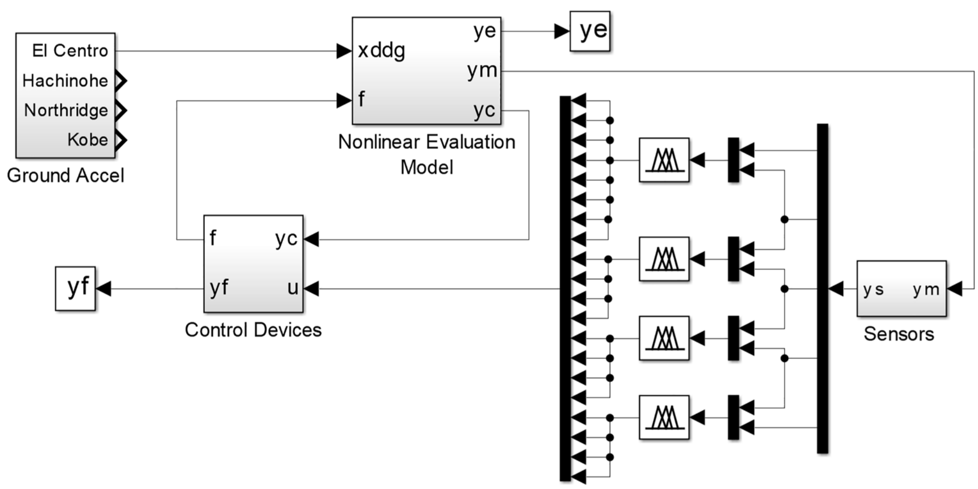

Fig. 9. Control scheme for the vibration control of the 20-story building.

Table 2
Fuzzy linguistic variables.

Variables	Definition
PVL	Positive and very Large
PL	Positive and Large
PM	Positive and Medium
PS	Positive and Small
PVS	Positive and very Small
ZR	Zero
NVS	Negative and very Small
NS	Negative and Small
NM	Negative and Medium
NL	Negative and Large
NVL	Negative and very Large

future challenge.

5. Problem statement

In this section, the optimization of fuzzy systems is described as a vibration control problem in building structures with active control systems. At first, the key characteristics of the considered building structures are described, while the fuzzy logic implementation in these structures as a control scheme is presented next. The evaluation criteria which are utilized to assess the overall performance of the optimization fuzzy control system are presented in detail accordingly, followed by presenting the optimization problem in which CryStAl is utilized as a metaheuristic algorithm.

5.1. Structural details

For numerical investigation purposes, two building structures with 3 and 20 stories are selected as design examples where they are 11.88 (m) and 80.77 (m) high, respectively. These two design examples are the benchmark control problems provided by Ohtori, *et al.* [55] to evaluate the performance of control systems in a standard way. The detailed specifications of these two structures are presented in Figs. 4 and 5.

Regarding the fact that most structural systems can experience large displacements, which may result in very large deformations in their structural elements, the linear concepts for analysis purposes cannot present accurate results when we deal with severe seismic inputs. Therefore, the possibility of the yielding of structural elements into nonlinear phases should be considered by employing a well-defined bilinear model, presented in Fig. 6 and Table 1 accordingly.

The seismic inputs of the considered buildings consist of the El Centro, Hachinohe, Northridge, and Kobe earthquakes as four well-known ground motions with Peak Ground Accelerations (PGA) of 3.417, 2.250, 8.267, and 8.178 m/s^2, respectively. The time histories for the acceleration of these earthquake records are presented in Fig. 7.

5.2. FLC implementation

Based on the presented details of the fuzzy logic controllers, there have to be control devices and sensors attached to the structure to implement the FLC as a control algorithm. For this purpose, active control devices implemented as tendons in the structures are used while 3 sensors and 3 actuators are also utilized for conducting control actions

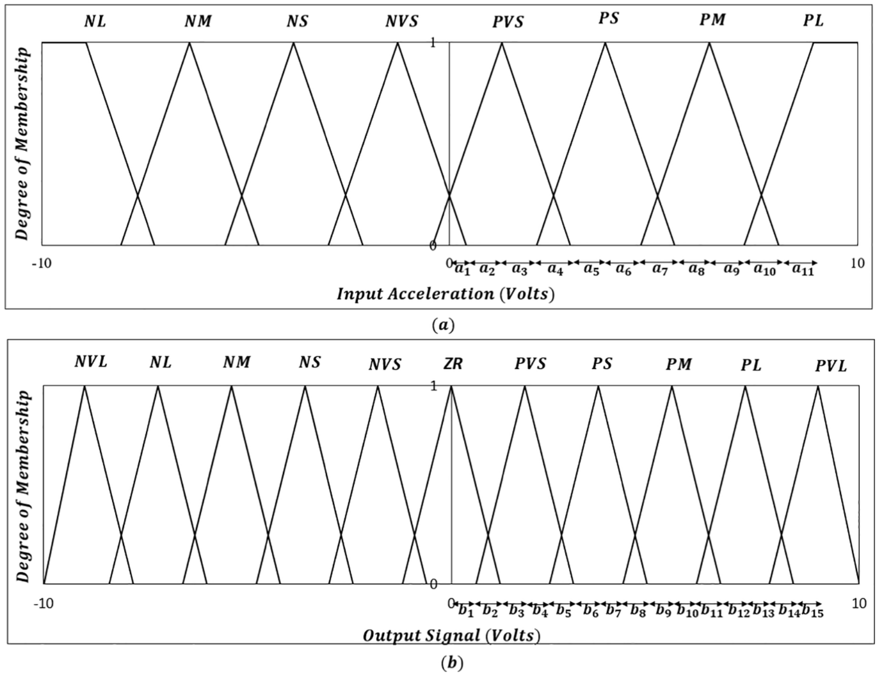

Fig. 10. The optimization variables of membership functions for the (a) fuzzy inputs and (b) fuzzy outputs.

Table 3
Optimization variables for the fuzzy rule base.

Control force								
Second input	**First input**							
	NL	***NM***	***NS***	***NVS***	***PVS***	***PS***	***PM***	***PL***
NL	*PVL/c1*	*PL/c9*	*PM/c17*	*PS/c25*	*PVS/c33*	*ZR/c41*	*NVS/c49*	*NS/c57*
NM	*PL/c2*	*PM/c10*	*PS/c18*	*PS/c26*	*PVS/c34*	*ZR/c42*	*NVS/c50*	*NS/c58*
NS	*PM/c3*	*PS/c11*	*PS/c19*	*PVS/c27*	*PVS/c35*	*ZR/c43*	*NVS/c51*	*NS/c59*
NVS	*PM/c4*	*PS/c12*	*PVS/c20*	*PVS/c28*	*ZR/c36*	*NVS/c44*	*NS/c52*	*NM/c60*
PVS	*PM/c5*	*PS/c13*	*PVS/c21*	*ZR/c29*	*NVS/c37*	*NVS/c45*	*NS/c53*	*NM/c61*
PS	*PS/c6*	*PVS/c14*	*ZR/c22*	*NVS/c30*	*NVS/c38*	*NS/c46*	*NS/c54*	*NM/c62*
PM	*PS/c7*	*PVS/c15*	*ZR/c23*	*NVS/c31*	*NS/c39*	*NS/c47*	*NM/c55*	*NL/c63*
PL	*PS/c8*	*PVS/c16*	*ZR/c24*	*NVS/c32*	*NS/c40*	*NM/c48*	*NL/c56*	*NVL/c64*

Table 4
Summary of the considered performance criteria.

Interstory drift ratio (IDR) $C_1 = \max_{7EQs}\left\{\frac{\max_{t,i}\frac{\lvert d_i(t)\rvert}{h_i}}{\delta^{max}}\right\}$	Level acceleration $C_2 = \max_{7EQs}\left\{\frac{\max_{t,i}\lvert\ddot{x}_{ai}(t)\rvert}{\ddot{x}_a^{max}}\right\}$	Base shear $C_3 = \max_{7EQs}\left\{\frac{\max_{t,i}\left\lvert\sum_i m_i\ddot{x}_{ai}(t)\right\rvert}{F_b^{max}}\right\}$
Ductility $C_4 = \max_{7EQs}\left\{\frac{\max_{t,j}\frac{\lvert\varphi_j(t)\rvert}{\varphi_{yj}}}{\varphi_{max}}\right\}$	Dissipated energy $C_5 = \max_{7EQs}\left\{\frac{\max_{t,j}\frac{\int dE_j}{F_{yj}\cdot\varphi_{yj}}}{E^{max}}\right\}$	Plastic connections $C_6 = \max_{7EQs}\left\{\frac{N_d^c}{N_d}\right\}$
Control force $C_7 = \max_{7EQs}\left\{\frac{\max_{t,l}\lvert f_l(t)\rvert}{W}\right\}$	Control device stroke $C_8 = \max_{7EQs}\left\{\frac{\max_{t,l}\lvert y_l^a(t)\rvert}{x^{max}}\right\}$	Control power $C_9 = \max_{7EQs}\left\{\frac{\max_t\lvert\sum P_l(t)\rvert}{\dot{x}^{max}}\right\}$

Table 5
Optimized evaluation criteria for the 3-story building associated with the El Centro earthquake.

	Metaheuristic approaches			
Criteria	**ALO** [13]	**JAYA** [13]	**ALO-JAYA** [13]	**CryStAl**
C_1	0.9478	0.9470	0.9431	**0.9250**
C_2	1.0354	1.0328	1.0568	**1.0324**
C_3	1.1475	**1.1101**	1.1792	1.2176
C_4	0.9778	0.9605	0.9629	**0.9548**
C_5	1.1531	1.1121	1.1200	**1.1112**
C_6	**1.0000**	**1.0000**	**1.0000**	**1.0000**
C_7	0.0244	0.0212	0.0226	**0.0205**
C_8	0.3746	0.3743	0.3727	**0.3656**
C_9	0.0178	**0.0153**	0.0197	0.0214

in the 3-story building, while for the 20-story one, a total number of 4 sensors and 20 actuators are utilized. For the 3-story building, three accelerometers are used in each story for sensing purposes, while three actuators with three fuzzy chips are implemented to perform the control actions. For the 20-story building, the sensors are on the 4, 8, 12, 16, and 20 stories. At the same time, the actuators are implemented in each of the story levels of the structure because only four fuzzy chips are utilized for calculating the control signals. The maximum control force that the actuators can provide in both structures is 1000 kN. The schematic presentations of the control schemes for the 3-story and 20-story structures are presented in Fig. 8 and Fig. 9, respectively.

In Figs. 8 and 9, a feedback control scenario is demonstrated for

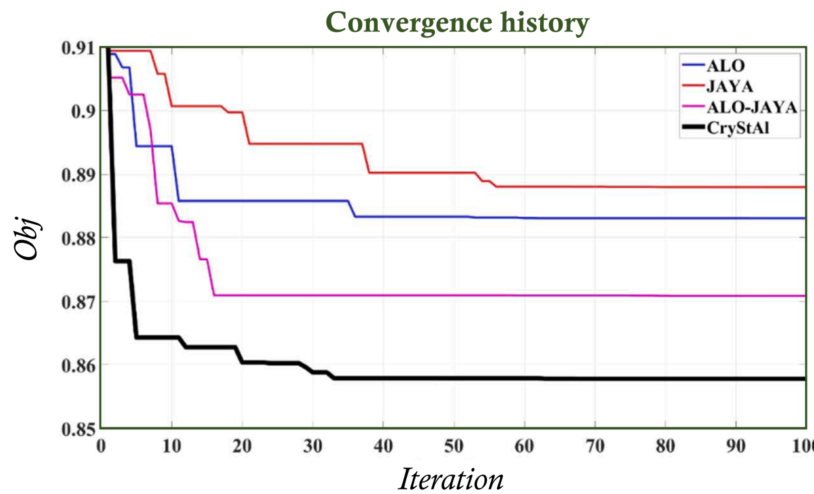

Fig. 11. Convergence history of *Obj* for the 3-story building.

Table 6
Optimized evaluation criteria for the 3-story building associated with the Hachinohe earthquake.

	Metaheuristic approaches			
Criteria	ALO [13]	JAYA [13]	ALO-JAYA [13]	CryStAl
C_1	0.9246	0.9489	0.9617	**0.9149**
C_2	0.9996	1.0137	1.0162	**0.9850**
C_3	1.0282	1.1115	1.0953	**1.0218**
C_4	0.7705	0.7795	0.8070	**0.7653**
C_5	0.1890	0.1596	0.2174	**0.1448**
C_6	0.9091	0.9091	0.9091	**0.6364**
C_7	**0.0145**	0.0251	0.0227	0.0252
C_8	0.3623	0.3718	0.3768	**0.3585**
C_9	**0.0164**	0.0290	0.0263	0.0266

Table 7
Optimized evaluation criteria for the 3-story building associated with the Northridge earthquake.

	Metaheuristic approaches			
Criteria	ALO [13]	JAYA [13]	ALO-JAYA [13]	CryStAl
C_1	0.9172	0.9295	0.9075	**0.8946**
C_2	1.1057	1.0893	1.0995	**1.0750**
C_3	1.1330	**1.1209**	1.1244	1.1251
C_4	0.9206	0.9049	0.8825	**0.8758**
C_5	0.9593	0.9427	**0.9272**	0.9358
C_6	**1.0000**	**1.0000**	**1.0000**	**1.0000**
C_7	0.0249	0.0254	0.0259	**0.0242**
C_8	0.3386	0.3431	0.3350	**0.3302**
C_9	0.0445	0.0423	**0.0416**	0.0480

Table 8
Optimized evaluation criteria for the 3-story building associated with the Kobe earthquake.

	Metaheuristic approaches			
Criteria	ALO [13]	JAYA [13]	ALO-JAYA [13]	CryStAl
C_1	0.8100	0.8045	0.7786	**0.7769**
C_2	0.8578	0.8977	0.8760	**0.8500**
C_3	1.1186	**1.1026**	1.1084	1.1085
C_4	0.8898	**0.8763**	0.8912	0.9054
C_5	0.9870	0.9432	0.9377	**0.9179**
C_6	0.9375	0.9375	0.9375	**0.8750**
C_7	0.0249	0.0256	0.0258	**0.0242**
C_8	0.3820	0.3794	**0.3672**	0.3805
C_9	0.0378	**0.0353**	0.0368	0.0396

conducting a vibration control act for the considered buildings in which *xddg* is the input acceleration signal of the buildings, *f* is the control force which is calculated through *u* as the control signal of the fuzzy logic controller, *ye* represents the structural responses, *ym* denotes the structural responses which is utilized as input signals of the fuzzy logic controllers, *yc* is the responses of the control devices implemented in the structure, and *yf* is the normalized responses of the control devices.

To configure a fuzzy control system, the linguistic variables should be utilized for converting crisp values to fuzzy ones. For this purpose, eleven fuzzy linguistic variables are considered, which can be found in Table 2.

In the 3- and 20-story buildings, accelerations of each story which are achieved from the implemented sensors are utilized as the inputs of the fuzzy controllers, while the control signals, which are utilized for determining the required control forces, are determined as the fuzzy outputs.

5.3. Optimization problem

An optimization problem is a minimization (or maximization) problem in which a predefined objective function is supposed to be minimized (or maximized). The objective function should be defined by means of some decision variables which can define each state of the system considered in the problem. In other words, optimization is the problem of tuning multiple variables to fulfill predefined objectives. To formulate a fuzzy optimization problem, decision variables are determined as the specific parameters that are utilized for the configuration of the fuzzy membership functions for inputs and outputs alongside the fuzzy rule base. Regarding the fact that tringles-shaped membership functions are utilized for the configuration of fuzzy inputs and outputs, $a_1, a_2, \cdots, a_{11}$ in Fig. 10.a denote the variables of the fuzzy inputs and b_1, $b_2, \cdots, b_{15}$ represent the optimization variables of the fuzzy outputs in Fig. 10.b. The fuzzy rule base utilizes 64 rules through 64 design variables $(c_1, c_2, \cdots, c_{64})$ which can be found in Table 3 (See Table 4).

As we aim to cover a wide range of responses of the two building structures, the optimization algorithms should be appropriately prepared to tune the predefined decision variables to reduce these responses. Based on the fact that some evaluation criteria were proposed for these benchmark design examples as represented in Table 5, the objective function is formulated in this paper using the first criterion regarding the maximum drift of the structures. The complete description of these criteria is presented in detail by Ohtori, *et al.* [55]. Furthermore, for completeness, the results of the earthquakes of this study are all considered using a weighted sum regarding the peak ground accelerations of these records as follows:

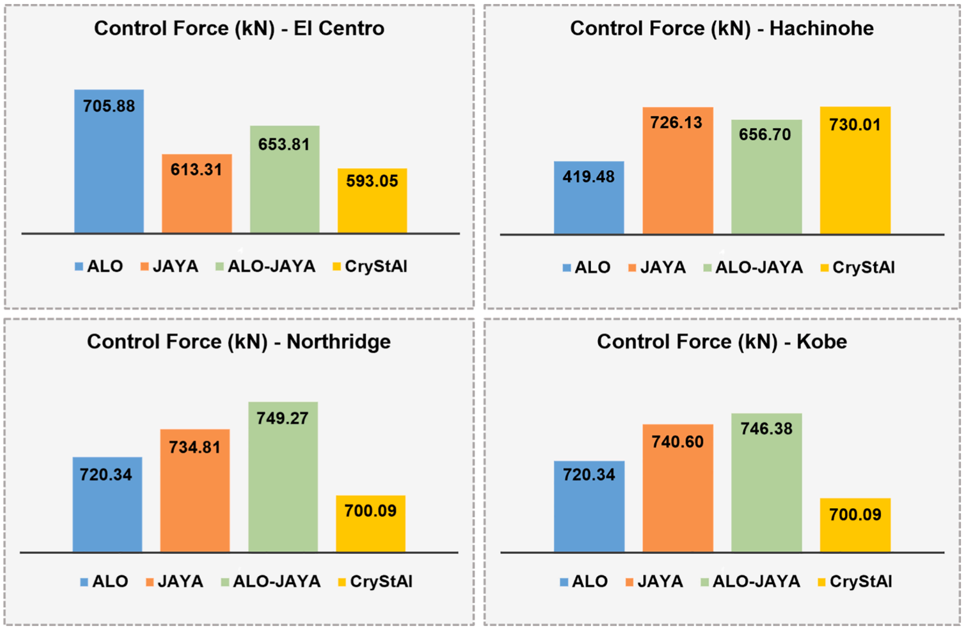

Fig. 12. Maximum required control forces in the 3-story building structure associated with different earthquakes.

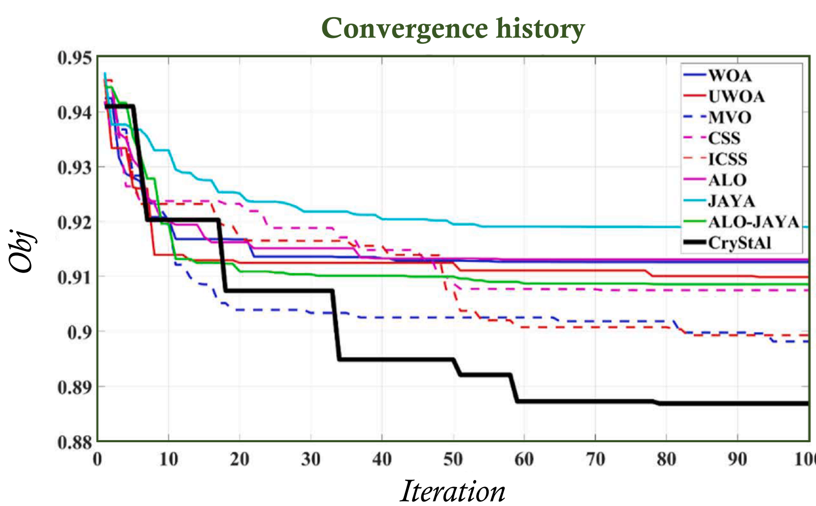

Fig. 13. Convergence history of *Obj* for the 20-story building.

Table 9
Optimized evaluation criteria for the 20-story building associated with the El Centro Earthquake.

	Metaheuristic approaches								
Criteria	**WOA** [12]	**UWOA** [12]	**MVO** [14]	**CSS** [15]	**ICSS** [15]	**ALO** [13]	**JAYA** [13]	**ALO-JAYA** [13]	**CryStAl**
C_1	0.9238	0.9580	0.9126	0.9223	0.9102	0.9241	0.9408	0.9072	**0.8908**
C_2	0.9375	0.9120	**0.8574**	0.9010	0.8838	0.8741	0.8943	0.8946	0.8813
C_3	0.9422	0.8632	0.8529	0.9107	0.8877	0.8735	0.8778	0.8871	**0.8519**
C_4	0.9832	0.9786	0.9599	0.9768	0.9631	0.9800	0.9749	0.9436	**0.9410**
C_5	–	–	–	—	—	—	—	—	—
C_6	–	–	–	—	—	—	—	—	—
C_7	0.0035	0.0022	0.0037	0.0023	0.0032	0.0027	0.0019	0.0024	**0.0016**
C_8	0.0986	0.0967	0.0980	0.0976	0.0958	0.0971	0.0972	0.0917	**0.0915**
C_9	0.0045	0.0023	0.0024	**0.0019**	0.0023	0.0020	0.0020	**0.0019**	0.0021

$$Obj = \frac{w_1(C_1)_{Elc} + w_2(C_1)_{Hachi} + w_3(C_1)_{North} + w_4(C_1)_{Kobe}}{w_1 + w_2 + w_3 + w_4} \tag{8}$$

where $(C_1)_{Elc}$ is the drift of the El Centro earthquake, $(C_1)_{Hachi}$ is the drift of the Hachinohe earthquake, $(C_1)_{North}$ is the drift of the Northridge earthquake, and $(C_1)_{Kobe}$ is the drift of the Kobe earthquake. $w_1 to w_4$ are the peak ground accelerations of the El Centro, Hachinohe, Northridge, and Kobe earthquakes which are set to be 3.41, 2.25, 8.26, and 8.17, respectively.

Table 10
Optimized evaluation criteria for the 20-story building associated with the Hachinohe Earthquake.

	Metaheuristic approaches								
Criteria	**WOA** [12]	**UWOA** [12]	**MVO** [14]	**CSS** [15]	**ICSS** [15]	**ALO** [13]	**JAYA** [13]	**ALO-JAYA** [13]	**CryStAl**
C_1	0.9666	0.9638	0.9584	0.9576	0.9472	0.9552	0.9554	0.9399	**0.9254**
C_2	1.0675	0.9629	0.9305	0.9363	0.9526	0.9436	0.9366	0.9902	**0.9225**
C_3	0.9989	0.9875	0.9933	0.9683	1.0326	**0.9477**	0.9675	1.0421	1.0053
C_4	0.9801	0.9700	0.9640	0.9568	0.9431	0.9665	0.9606	0.9600	**0.9298**
C_5	–	–	–	—	—	—	—	—	—
C_6	–	–	–	—	—	—	—	—	—
C_7	0.0035	0.0022	0.0028	0.0021	0.0017	0.0021	0.0019	0.0017	**0.0014**
C_8	0.0772	0.0786	0.0780	0.0780	**0.0758**	0.0780	0.0762	0.0769	0.0772
C_9	0.0015	**0.0010**	0.0016	**0.0010**	0.0016	0.0011	**0.0010**	0.0013	0.0014

Table 11
Optimized evaluation criteria for the 20-story building associated with the Northridge Earthquake.

	Metaheuristic approaches								
Criteria	**WOA** [12]	**UWOA** [12]	**MVO** [14]	**CSS** [15]	**ICSS** [15]	**ALO** [13]	**JAYA** [13]	**ALO-JAYA** [13]	**CryStAl**
C_1	1.0026	0.9963	0.9799	1.0032	0.9946	1.0096	1.0039	1.0087	**0.9783**
C_2	1.0094	0.9851	1.0078	0.9882	0.9823	0.9799	0.9670	0.9800	**0.9614**
C_3	**0.8925**	0.9590	0.9580	0.9468	0.9621	0.9458	0.9696	0.9673	0.9827
C_4	1.0059	1.0035	1.0186	1.0216	1.0180	1.0176	1.0202	1.0045	**0.9969**
C_5	1.0267	0.9947	1.0374	0.9765	**0.9154**	1.0164	1.0177	1.0410	0.9927
C_6	**1.0000**	**1.0000**	1.0104	1.0208	1.0208	1.0104	**1.0000**	1.0104	1.0208
C_7	0.0055	0.0057	0.0059	0.0048	0.0045	0.0063	0.0040	0.0057	**0.0038**
C_8	0.1091	0.1060	0.1070	0.1093	0.1089	0.1092	0.1089	0.1077	**0.1053**
C_9	0.0071	0.0033	0.0046	0.0039	0.0040	0.0034	**0.0030**	0.0044	0.0039

Table 12
Optimized evaluation criteria for the 20-story building associated with the Kobe Earthquake.

	Metaheuristic approaches								
Criteria	**WOA** [12]	**UWOA** [12]	**MVO** [14]	**CSS** [15]	**ICSS** [15]	**ALO** [13]	**JAYA** [13]	**ALO-JAYA** [13]	**CryStAl**
C_1	0.8022	0.7876	0.7930	0.7908	0.7853	0.7994	0.8141	0.7993	**0.7822**
C_2	0.9892	0.9507	0.9857	0.9339	0.9110	0.9553	0.9513	0.9528	**0.9108**
C_3	0.9570	0.9269	**0.9131**	0.9229	0.9330	0.9423	0.9216	0.9219	0.9422
C_4	0.7536	0.7539	0.7781	0.7620	0.7359	0.7536	0.7692	0.7645	**0.7328**
C_5	0.9787	0.9358	0.9236	0.9352	0.9183	0.9816	1.0099	0.9794	**0.9064**
C_6	0.9951	0.9881	1.0000	0.9762	**0.9643**	1.0119	1.0000	0.9762	**0.9643**
C_7	0.0061	0.0055	0.0068	0.0048	0.0052	0.0064	**0.0040**	0.0065	0.0075
C_8	0.1258	0.1236	0.1244	0.1240	0.1232	0.1254	0.1277	0.1254	**0.1227**
C_9	0.0092	0.0052	0.0055	0.0048	0.0055	0.0056	**0.0037**	0.0053	0.0058

6. Numerical results

In this section, the results of the CryStAl algorithm in dealing with the mentioned fuzzy optimization problems are investigated, while the results of other approaches from the literature are also provided to make a valid judgment. In Fig. 11, the convergence history of CryStAl and other approaches are presented for the predefined *Obj* as the objective function regarding the 3-story building. It can be concluded that CryStAl is capable of providing 0.8578 for the objective functions, which is the best among other approaches, while the Hybrid Ant Lion Optimizer-Jaya (ALO-JAYA) [13] with 0.8708, Ant Lion Optimizer (ALO) [13] with 0.8831, and Jaya [13] with 0.8879 have the second to fourth ranks.

In Tables 5 to 8, the evaluation criteria which are utilized for performance estimation of the optimally tuned fuzzy controllers implemented in the 3-story building are presented for different seismic inputs. It can be seen that CryStAl has a better performance in most of the considered cases.

Given that in active vibration control systems the total control force, provided through the actuators, have multiple limitations, metaheuristic algorithms are supposed to reduce the amount of this force during the optimization process, knowing that the main objective of the optimum design scheme is not the control force. In Fig. 12, the maximum required control force in the 3-story building structure is presented in which the capability of different approaches in reducing the overall amount of the control force in this building is in perspective. It can be concluded that CryStAl is capable of providing the lowest values for El Centro (593.05 kN), Northridge (700.09 kN), and Kobe (700.09 kN). Moreover, for Hachinohe, the result of CryStAl is very competitive.

For the 20-story building, the convergence history for the *Obj* is presented in Fig. 13, while the CryStAl with 0.8869 outranks the other approaches, including the Whale Optimization Algorithm (WOA) [12] with 0.9127, Upgraded WOA (UWOA) [12] with 0.9099, Multi-Verse Optimizer (MVO) [14] with 0.8981, Charged System Search (CSS) [15] with 0.9075, Improved CSS (ICSS) [15] with 0.8993, ALO-JAYA [12] with 0.9085, ALO [13] with 0.9131 and Jaya [13] with 0.9190.

In Tables 9–12, the evaluation criteria which are utilized for the performance evaluation of the optimally-tuned fuzzy controllers implemented in the 3-story building are presented for different seismic inputs. As can be seen from these results, CryStAl has a better performance in the majority of the considered cases.

In Fig. 14, the maximum required control force in the 20-story building structure is presented, in which the capability of different approaches in reducing the overall value of the control force in this building is considered. It can be concluded that CryStAl is capable of providing the lowest amount of 170.01 kN for El Centro, 156.34 for Hachinohe, 412.91 for Northridge, while for Kobe, the result of CryStAl

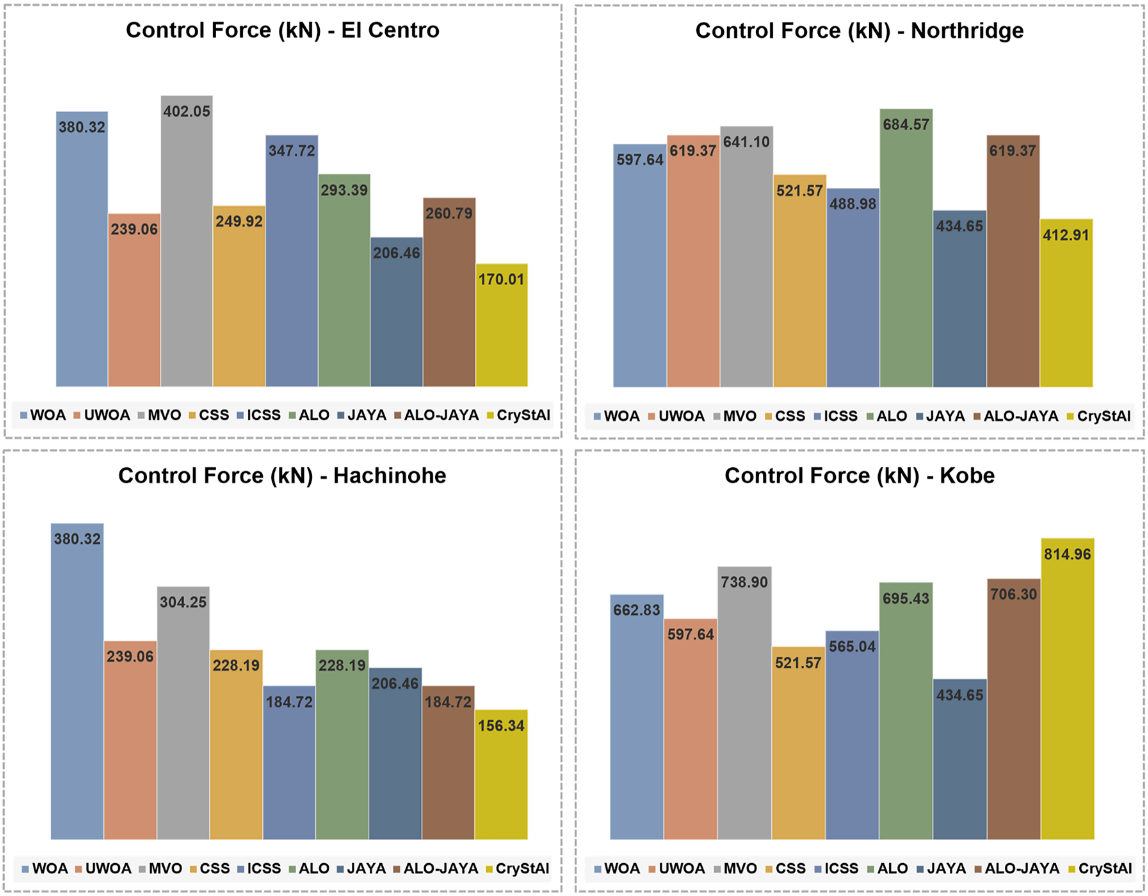

Fig. 14. Maximum required control forces in the 20-story building structure associated with different earthquakes.

is very competitive.

7. Summary of results and concluding remarks

This paper presented the optimization of fuzzy logic controllers in building structures where the application of a range of metaheuristic algorithms for the performance enhancement of these intelligent systems was examined and evaluated. The Crystal Structure Algorithm (CrystAl) was utilized as the primary optimization algorithm in which the fundamental principles of crystal structures, including the lattice and basis in their geometric configurations, are the underlying inspirational concepts. Two 3-story and 20-story real-size building structures were used for numerical investigations. At the same time, fuzzy controllers were implemented through an active control system to intelligently control the seismically-induced vibration of the structures. By conducting nonlinear structural analyses, the ductility, energy dissipation, and other nonlinear characteristics of the structures were also considered as structural responses to be controlled. The results of CrystAl were compared with those of other expert systems from the literature, where we observed that CrystAl is capable of outranking the other methods in most cases. The main results obtained from this study are summarized as follows:

- For the 3-story building, CrystAl provided 0.8578 for the objective functions, which was the best among all the approaches, while ALO-JAYA with 0.8708, ALO [13] with 0.8831, and Jaya [13] with 0.8879 had the second to fourth ranks.
- Concerning the maximum required control force, CrystAl provided the lowest amounts of force which were 593.05 kN for El Centro, 700.09 for Northridge, and 700.09 for Kobe, while for Hachinohe the result of CrystAl was very competitive.
- For the 20-story building, CrystAl with 0.8869 outranked the other approaches including WOA [12] with 0.9127, UWOA [12] with 0.9099, MVO [14] with 0.8981, CSS [15] with 0.9075, ICSS [15] with 0.8993, ALO-JAYA [13] with 0.9085, ALO [13] with 0.9131, and Jaya [13] with 0.9190.
- For this building, CrystAl produced the lowest amounts of control force as 170.01 kN for El Centro, 156.34 for Hachinohe, and 412.91 for Northridge, while for Kobe the result of CrystAl was again very competitive.
- Furthermore, CrystAl produced the lowest amounts of force which were 593.05 kN for El Centro, 700.09 for Northridge, and 700.09 for Kobe, while the result of CrystAl for Hachinohe turned out to be competitive.
- It was observed that CrystAl delivered the lowest amounts of force which were 170.01 kN for El Centro, 156.34 kN for Hachinohe, and 412.91 kN for Northridge, while offering a highly competitive outcome for Kobe.

The findings of this research revealed that, in the majority of cases, the results from CrystAl were more accurate in comparison with those produced by the other metaheuristic optimization methods. This motivates the exploration of potential applications of CrystAl for solving problems in other fields of engineering. Importantly, given that two benchmark building structures are considered as design examples in this paper, all of the complex details of the problems should be determined based on the main reference [55] in order to have a fair judgment about the capability of the selected metaheuristic algorithm. However, the possibility of increasing the seismic inputs to evaluate the capability of the considered methods in dealing with different types of earthquakes can be considered as a future challenge.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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