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Enhancing Seismic Design of Non-structural Components Implementing Artificial Intelligence Approach: Predicting Component Dynamic Amplification Factors

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A B S T R A C T

The seismic performance of non-structural components (NSCs) has been the focus of intensive study during the last few decades. Modern building codes define design forces on components using too simple relationships. The component accelerates faster than the floor acceleration to which it is connected. Therefore, component dynamic amplification factors (CDAFs) are calculated in this work to quantify the amplification in the acceleration of NSCs for the various damping ratios and tuning ratios of the NSC, and the primary structural periods. From the analysis results, it was observed that CDAF peaks are either underestimated or overestimated by the code-based formulae. A prediction model to ascertain the CDAFs was also developed using artificial neural networks (ANNs). Following that, the suggested model is contrasted with the established relationships from the past research. The ANN model's coefficient of correlation (R) was 0.97. Hence, using an ANN algorithm reduces the necessity of laborious and complex analysis.

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1. INTRODUCTION

Non-structural components (NSCs) cannot withstand loads [1]. Non-structural components damage may cause both immediate and long-term financial losses. The damage of components, especially expensive and important equipment in important structures may impair the functionality of buildings [2-5]. These results show that NSC seismic performances are just as significant as structural component seismic performances. The current Standards and Guidelines were mostly produced using empirical methodologies built from earlier experiences and engineering skills [6]. To keep NSCs secure and guarantee that the building can remain operating after an earthquake, non-structural components must be constructed for earthquakes. To do this, it is necessary to calculate the floor response spectrum (FRS) at the location where the NSC is connected to the main system.

Using a decoupled analysis method, the floor response spectrum (FRS) approach, is used [7-15]. Without considering the impact of the secondary system, the fundamental structure is dynamically analyzed first. The time history of the acceleration response is supplied to a component at floor level where it is mounted to create the FRS. The resulting FRS may thus be used to determine the maximum force for the NSCs. According to research on dynamic behaviour of components subjected to ground motion, the likelihood of NSC damage would be enhanced if the primary structure's response was amplified [16]. Researchers began studying FRS generating methods in the 1970s. A method for producing the FRS using the ground response spectra was created by Yasui et al. [17]. For the purpose of accurately identifying floor acceleration spectra, a unique method is created and verified [18]. To study the seismic requirements on nuclear plants, Jiang et al. [19] created

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floor response spectra. They found that the FRS from analysis showed significant fluctuations, especially in tuning circumstances. Investigations have been done on the floor response spectrum of complex structures [20-24]. The most recent research [25] investigated how a stiffness irregularity affected the FRS and found that the floor response's amplitude is larger at the soft story position. None of the FRS generating approaches that have been extensively discussed in the relevant literature [19, 23, 26, 27] can reliably measure the amplification in the acceleration of the non-structural components.

Component dynamic amplification factors, which represent the amplification of NSCs, are significant in the production of FRS. Hence, using a component dynamic amplification factor, the current work investigates how to quantify such amplification. Hence, for primary structures subject to seismic loads, the aforementioned factors were examined. The amplification factors and those discovered from the code-based formulations were contrasted. An attempt has been made in this study to develop the prediction model for the CDAF. The existing models [28, 29] for the determination of CDAF have not been considered the effect of a damping ratio of the NSC. As a result, this study proposed a prediction model for the CDAF spectrum based on data-driven methods. Data-driven methods like Machine learning (ML) techniques are superior in the establishment of relations between various input and output variables than conventional regression analysis [10, 30-32]. To be more specific, an ML model including Artificial Neural Network (ANN) was utilized to develop the CDAF spectra. By contrasting the amplification factors computed from the ML model with the factors acquired from the existing relations, the constructed prediction model based on the ML technique was verified.

The following is how the paper is organized: In section 2, the mathematical model is described. The selection and scale of ground motions are shown in section 3. The CDAF is described in section 4. The ANN model's details are presented in section 5. The suggested ANN prediction model's validation is shown in section 6. The final part draws brief conclusions (i.e., section 7).

2. DESCRIPTION OF MODEL

The basic structure in the current investigation is an acceleration sensitive NSC linked to a SDOF, as shown in Figure 1. The primary structure's (ξ_p) viscous damping ratio is taken as 5%. It is possible to calculate the primary structure's reaction for a given set of ground movements using Equation (1).

$$m_p\ddot{x} + c_p\dot{x} + k_p x = -m_p\ddot{x}_g \tag{1}$$

where m_p, c_p, and k_p are the mass, damping and stiffness for the primary structure: $c_p = 2m_p\xi_p\omega_p$; ω_p is the primary structure's frequency; $\dot{x}$ and $\ddot{x}$ are the relative velocity and acceleration; $\ddot{x}_g$ is the ground acceleration; $(\ddot{x} + \ddot{x}_g)$: primary structure's absolute acceleration. The resulting absolute acceleration response may be transformed into pseudo-acceleration response spectra in accordance with Equation (2) produce the FRS.

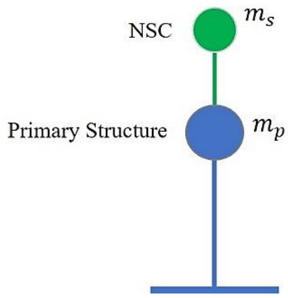

Figure 1. Primary structure connected with non-structural component

$$m_s\ddot{x}_s + c_s\dot{x}_s + k_s x_s = -m_p(\ddot{x} + \ddot{x}_g) \tag{2}$$

where m_s, c_s, and k_s are the mass, damping, and stiffness for the NSC: $c_s = 2m_s\xi_s\omega_s$; ω_s and ξ_s are the NSC's frequency and damping ratio; x_s, $\dot{x}_s$, and $\ddot{x}_s$, are the relative displacement, velocity, and acceleration, respectively. Equations (1) and (2) are differential equations, which are then solved numerically using the Runge-Kutta technique.

3. GROUND MOTIONS

Realistic responses are produced by the seismic response evaluation process using actual ground motion recordings [33-38]. Such records are easily accessible through the NGA-West 2 Database of the Pacific Earthquake Engineering Research Centre (PEER) [39]. Hence, 11 horizontal ground motion excitations have been taken into account in the current research for the hard soil type in accordance with ASCE 7-16 [28]. Based on shear wave velocity (V_{S30}), ground motions are chosen to depict hard soil in accordance with National Earthquake Hazard Reduction Program (NEHRP) [40] criteria. Table 1 displays the specifics of the excitation. Since they can greatly reduce the computational time compared to many ground motions, spectrum compatible ground motions are used in this investigation [41]. To create spectrum-compatible seismic excitations, the time-domain spectral matching method [42] is applied. The IS 1893:2016 target spectra and average spectra of ground motions are shown in Figure 2. The average spectrum must remain above 90% of the target spectrum in accordance with ASCE 7-16. This figure shows that mean spectra are much more than 90% of the target spectra.

TABLE 1. Ground motions information

Earthquake	Year	Station	M_w	R_{jb} (km)
Helena_ Montana-01	1935	Carroll College	6	2.07
Helena_ Montana-02	1935	Helena Fed Bldg	6	2.09
Kern County	1952	Pasadena - CIT Athenaeum	7.36	122.65
Kern County	1952	Santa Barbara Courthouse	7.36	81.3
Kern County	1952	Taft Lincoln School	7.36	38.42
Southern Calif	1952	San Luis Obispo	6	73.35
Parkfield	1966	Cholame - Shandon Array #12	6.19	17.64
Parkfield	1966	San Luis Obispo	6.19	63.34
Parkfield	1966	Temblor pre-1969	6.19	15.96
Borrego Mtn	1968	Pasadena - CIT Athenaeum	6.63	207.14
Borrego Mtn	1968	San Onofre - So Cal Edison	6.63	129.11

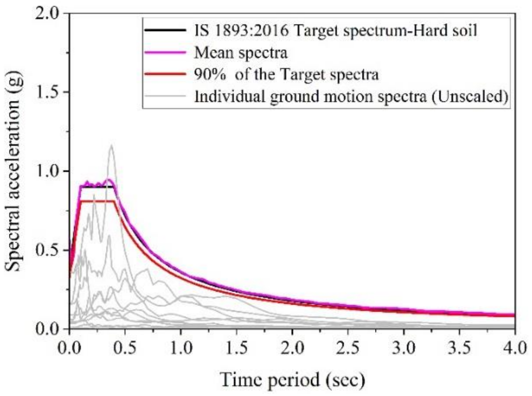

Figure 2. Mean and target spectra

4. COMPONENT DYNAMIC AMPLIFICATION FACTOR

The component's acceleration in relation to the floor acceleration is examined in this section. Elastic SDOF systems make up the NSCs examined in this study. In comparison to the main structure, the NSC's mass is thought to be quite low. Floor response spectra (FRS) is a decoupled approach that evaluates the primary system and non-structural component separately in a predetermined sequence. The linear time history analysis's input is scaled ground motions. From the model at the floor, absolute acceleration responses are collected and fed into the NSC to produce the relevant FRS. With a 5% damping ratio, the FRS was attained. The FRS is performed, and its results are normalized by the appropriate peak floor acceleration (PFA). The component dynamic amplification factor is represented by the ratio FRS/PFA (CDAF). Understanding the seismic behaviour of non-structural components requires knowledge of the CDAF [12, 13]. Figure 3 shows the CDAF spectra for different primary structural periods for a 5% damping ratio of the NSC. The vibration period (T_p) of the primary structures shown in the Figure 3 represent the very stiff to flexible structures. The peak in the CDAF spectra was observed in the range of $0.7 \leq T_s/T_p \leq 1$ for the considered primary structures. The definitions of ASCE 7-16 [28] are contrasted with the CDAF in the present study. According to ASCE 7-16, for flexible NSCs with vibration periods greater than 0.06 seconds, the components amplification factor (a_p) is 2.5. The value of the amplification factor for stiff NSCs ($T_s < 0.06$ sec) is 1. It is clear from Figure 3 that the CDAF peaks are either underestimated or overestimated by the ASCE 7 standards.

Since NSCs come in a variety of periods and damping ratios (ξ_s), it is necessary to evaluate the impact of these characteristics on the seismic behaviour of non-structural components [43]. Determining component dynamic amplification factors for various ξ_s (0.1%, 0.2%, 0.5%, 1%, 2%, 5%, and 10%) is the purpose of this work. The CDAF spectrum for various damping ratios (0.1%, 2%, and 10%) is shown in Figure 4. As predicted, lower ξ_s values led to greater amplification factor values. The damping ratio of NSC is discovered to have a greater impact on the main structure's vibration periods. It is important to note that the impact of ξ_s is negligible for both extremely short and very long NSC periods. To do so, this work tried to create a prediction model for the CDAF utilizing machine learning methods such as artificial neural networks (ANNs). Amplification factors were determined for various ξ_s (0.1%, 0.2%, 0.5%, 1%, 2%, 5%, and 10%), tuning ratios, T_s/T_p (0 to 40 with 0.5 increment), and primary structural periods, T_p (0.1 to 1 s, with 0.1 increment, and 1.25, 1.5, 2, 2.5, 3, 3.5, and 4 s).

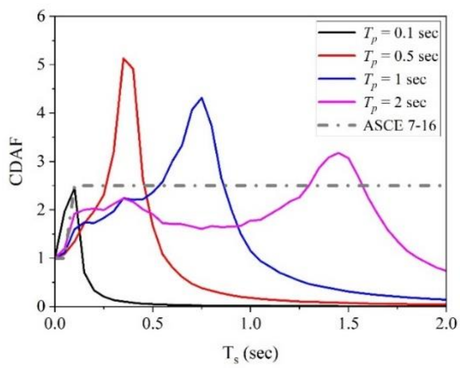

Figure 3. Component dynamic amplification factors for different primary structural periods

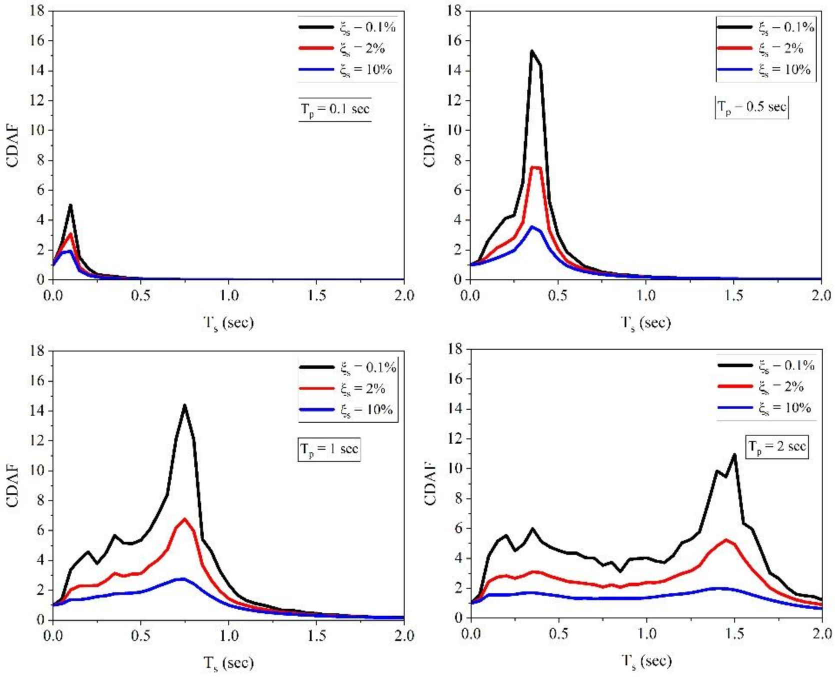

Figure 4. Component dynamic amplification factors at different NSC damping ratios

5. ARTIFICIAL NEURAL NETWORK (ANN) MODEL

Biological neural networks are simplified models that are used to express ANNs analytically. Massive data sets, difficult problems, and muddled circumstances may all be handled by neural networks. Because of this, neural networks are frequently a more accurate instrument for forecasting than traditional computational methods [44]. The current study employs a two layered feed-forward neural network to precisely forecast the CDAF. One of two levels, the other being the output layer, is the hidden layer. With only one hidden layer, neural networks can accurately estimate any function [45]. The tuning ratio (T_s/T_p), damping ratio (ξ_s) of the NSC, and primary structural period (T_p) are all considered as model inputs. The predicted output of the model is represented by the CDAF values. The performance of the model is more strongly influenced by the architecture of the networks. Insufficient hidden neurons will make learning harder for the network. Yet, the likelihood of the network overfitting the training set increases with the number of hidden neurons. By experimenting with the number of hidden neurons, we were able to fix the set with the lowest mean squared error (MSE). The optimal number was determined to be 35 hidden nodes, which corresponds to that number. Consequently, the 35 neurons in the hidden layer were considered while creating the ANN 3-35-1 model (Figure 5). The hidden neurons must be trained using an appropriate learning method. The network is trained using the Bayesian Regularization (BR) back propagation (BP) method. Moreover, the output and hidden layers both employ the Tan-sigmoid transfer function. Using the MATLAB R2019b environment, the neural network model for this investigation was developed. In all, 9639 CDAF values representing 17 primary structural periods, 81 NSC tuning ratios, and 7 NSC damping ratios were generated by simulation in this work. A training set, which makes up 70% of the whole dataset, and a testing set, which makes up 30% of the total dataset, are further separated into each dataset. The complete dataset must be pre-processed before training. The dataset must be normalized between -1.0 and 1.0 to give the variables an

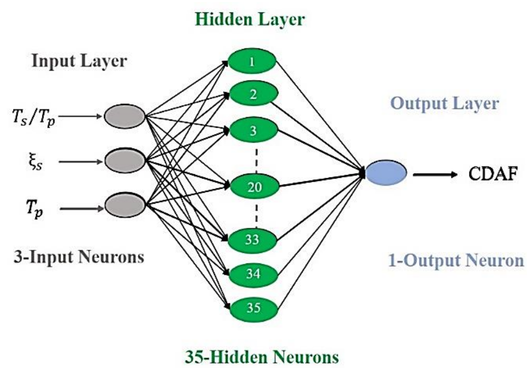

Figure 5. ANN 3-35-1 model

equal weight. Using Equation (3), this normalization may be carried out.

$$x_n = \frac{2(x - x_{min})}{(x_{max} - x_{min})} - 1 \tag{3}$$

where x_n is the normalized value. x_{min}, x_{max}, are the minimum and maximum values of the variable x, respectively. By specifying the performance assessment functions, the ANN model's predictive power is assessed. In this study, performance was measured using the mean square error (MSE), and coefficient of correlation (R). The performance functions (Equations (4) and (5)) are defined as follows:

$$MSE = \frac{\sum(y_s - y_p)^2}{N} \tag{4}$$

$$R = \sqrt{\frac{\sum y_s^2 - \sum(y_s - y_p)^2}{\sum y_s^2}} \tag{5}$$

where, N is the number of data points, and y_s and y_p are the simulated and predicted outputs. Table 2 displays the model's performance results. The error (MSE) should be as low as feasible, and the R value ought to be high. The connection between the predicted CDAF and the simulated CDAF is shown in Figure 6. The component dynamic amplification factor values are accurately predicted by the model, as seen by the correlation coefficient's proximity to unity.

6. VALIDATION OF THE ANN PREDICTION MODEL

This section looked at how well the ANN model predicted the dynamic amplification factors of non-structural parts that were connected to the main structure. For this validation, the damping ratios of NSC (0.6% and 3%) were used to construct the CDAF spectra of the primary structure under consideration. The ANN prediction model is not developed using the damping ratio values that were taken into consideration for validation. The predicted and simulated CDAF spectra are displayed in Figure 7. The predicted and simulated spectra for each of the instances under consideration have a comparably high level of agreement. Table 3 displays the maximum and lowest parameters used in creating the

TABLE 2. Results of the ANN model's performance

Dataset	R	MSE
Training	0.974	0.0019
Testing	0.966	0.0022

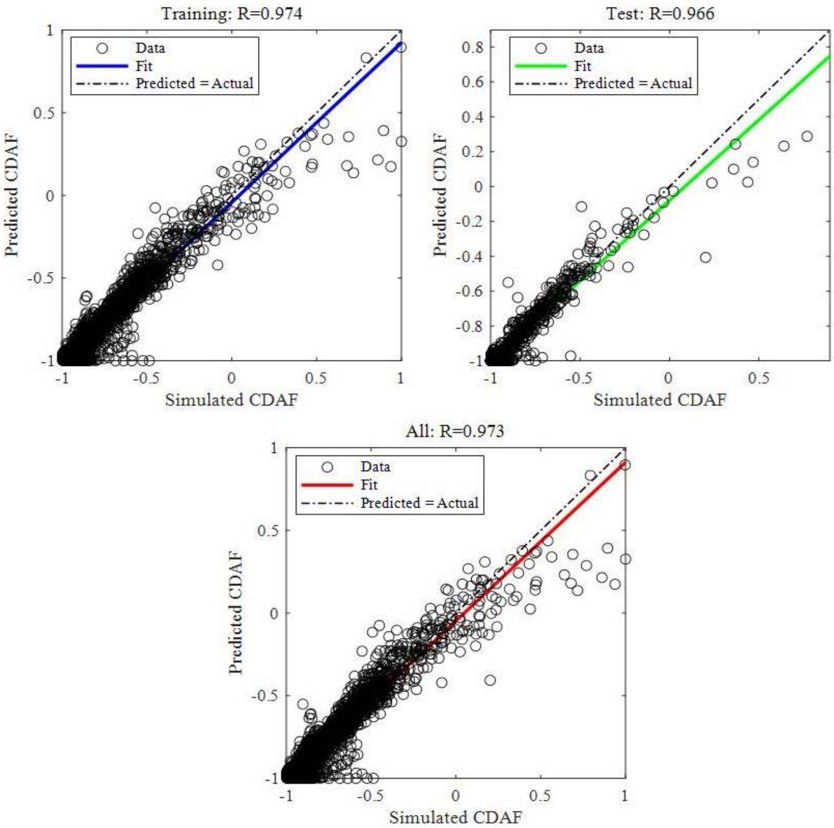

Figure 6. CDAF predicted by ANN and simulations

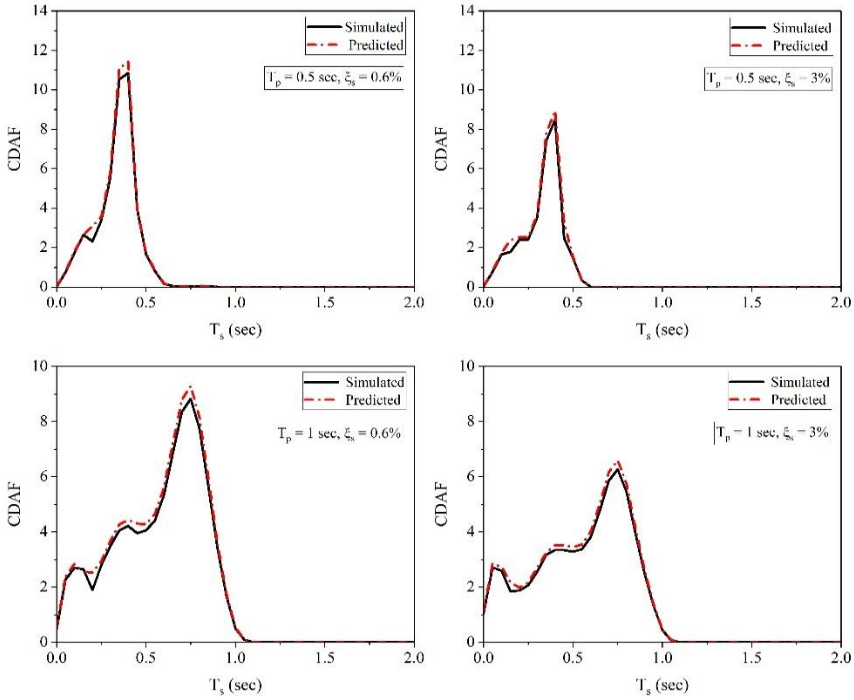

Figure 7. Comparison of simulated and ANN's predicted CDAF spectra

TABLE 3. Limits of various variables

	Input variables			Output
	T_p **(sec)**	T_s/T_p	ξ_s (%)	**CDAF**
Max	4.0	40.0	10.0	19.598
Min	0.1	0.00	0.1	0.000

ANN model. Thus, neural networks may be used to analyze the seismic behaviour of non-structural components. The ANN analysis approach reduces computational time by skipping the typical complicated analysis.

7. CONCLUSIONS

Component dynamic amplification factors are crucial because they represent the amplification of NSCs in the floor response spectrum. Hence, the present study explores the quantification of such amplification by means of a component dynamic amplification factor. The primary structure is therefore examined for the aforementioned factors. The amplification factors are compared to those found in the code-based formulae. The study allows for the following conclusions to be drawn:

- The component dynamic amplification factors show significant peak values in the range of $0.7 \leq T_s/T_p \leq 1$ for the considered primary structures.
- The damping ratio (ξ_s) of NSC has a greater impact on the dynamic amplification factors at vibration periods of the primary structure.
- The influence of ξ_s is negligible for both extremely short and very long NSC periods.
- The ASCE 7's definition under- or overestimates the amplification factors for periods closer to the vibration periods of the primary structure. So, the impacts of the dynamic properties of the NSC and primary structure should be included in the present code-based formulation.
- Machine learning (ML) technique like ANN is utilized to develop the prediction model for CDAF spectra. ANN is proved to be more effective and powerful tool in this study for establishing the relation between the input and output variables.

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Persian Abstract

چکیده

عملکرد لرزه ای اجزای غیر سازه ای در طول چند دهه اخیر مورد توجه محققین بوده است. قوانین ساختمانی نوین، نیروهای طراحی را بر روی اجزا با استفاده از روابط بسیار ساده تعریف می کنند. معمولا اجزای غیرسازه ای متصل به یک کف سازه ای شتابی بیشتر از طبقه ای که به آن متصل هستند می گیرند. بنابراین، ضرایب تشدید دینامیکی اجزا در این کار برای کمی سازی میزان تشدید در شتاب اجزای غیر سازه ای برای نسبت‌های مختلف میرایی و نسبت‌های تنظیم شده اجزای غیر سازه ای، و پریودهای ارتعاشی اصلی سازه محاسبه می‌شوند. از نتایج تجزیه و تحلیل به دست آمده، مشاهده شد که نقاط پیک CDAF توسط فرمول‌های مبتنی بر آیین نامه های فعلی مقادیر را دست پایین در نظر گرفته یا بیش از حد برآورد می‌نمایند. برای رفع این مشکل، یک مدل پیش‌بینی برای تعیین CDAFs با استفاده از شبکه‌های عصبی مصنوعی (ANN) توسعه داده شده است. ضریب همبستگی مدل 0.97 بود. از این رو، استفاده از یک الگوریتم ANN ضرورت تجزیه و تحلیل پیچیده را تا حد قابل توجهی کاهش می دهد.