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# Evaluation of a Swarm Intelligence Approach for Assessing Civil Infrastructure Condition

[1]Hemal Thakker, [2]Daljeet Pal Singh, [3]Raja Praveen K. N., [4]Tannmay Gupta, [5]Ravi Kant Pareek

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**Abstract:** It is crucial to evaluate the state of civil infrastructure to maintain the durability of these essential systems and ensure public safety. Physical assessments, which are time-consuming, laborious, and prone to human error, are frequently used in traditional methods for evaluating infrastructure status. This study introduces a new Swarm-Intelligent Aquila Optimisation (SIAO) method for assessing the state of civil infrastructure to get beyond these restrictions. The SIAO approach intelligently examines and evaluates the present condition of buildings by examining many characteristics, including structural health, by simulating a swarm's well-organized motion and decisions. Concrete image datasets are gathered to explore the proposed SIAO approach's performance in monitoring the structures' status. The outcomes showed that the SIAO technique performs better than conventional methods in effectiveness, accuracy, and dependability. This strategy could revolutionize the building engineering discipline and support the proactive control and upkeep of vital infrastructure facilities..

***Keywords:*** *Civil infrastructure, condition monitoring, structural health, Swarm-Intelligent Aquila Optimization (SIAO)*

## 1. Introduction

The ability to identify concealed damage in a structure makes monitoring the health of civil engineering buildings one of the most recent research trends [1]. Numerous methods for spotting damage have been developed, some of which are modal-based, like the strain energy method, frequency response method, and mode shape methods and their derivatives. These modal-based techniques primarily use frequency ranges and shape of modes as structural characteristics to find deterioration in bridges and other civil engineering structures. New techniques, such as those based on power spectral analysis, deflection analysis, and non-negative matrix factorization, have been developed that employ vibration structure data for damage analysis [2]. These algorithms are effective in detecting damage. Utilizing the data from the acceleration sensor, various wavelet-based techniques have also been created that can identify structural damage.

However, as was seen from earlier research studies, the majority of the approaches utilized might be appropriate for localizing damage, but there aren't many methods accessible for estimating the extent of damage to a structure [3]. The severity of a structure's damage can now be evaluated using model update methods, neural network-based methodologies, and optimization techniques. These algorithms employ a variety of search methods to find the best answer within the given parameters. The main reason why researchers favor optimization techniques is that they require less computation time to detect structural degradation.

The simplicity, flexibility, derivation-free process, and local optima avoidance of the algorithms' interface have helped meta-heuristic optimization techniques become quite popular [4]. Two categories of meta-heuristic algorithms can be distinguished: a single solution based, which utilizes one potential solution to be optimized throughout iterations, and crowd built, which uses an initial set of numerous answers to optimize and converge.

Four different categories have been established within the meta-heuristic optimization strategies: physical-based, evolutionary-based, swarm intelligence (SI), and human-based procedures [5]. Traditional methods for assessing infrastructure status usually employ physical assessments, which are tedious, time-consuming, and subject to human mistake. To get over these limitations, this study presents a novel Swarm-Intelligent Aquila Optimisation (SIAO) technique for evaluating the health of civil infrastructure. To get around these limitations, this work introduces a novel Swarm-Intelligent Aquila Optimisation (SIAO) technique for evaluating the health of civil infrastructure.

The remaining divisions of this article are as follows: Part 2 introduces related works, Part 3 discusses the methodology,

[1]*Department of ISME, ATLAS SkillTech University, Mumbai, Maharashtra, India, Email Id- hemal.thakker@atlasuniversity.edu.in, Orcid Id- 0009-0002-0043-5760*
[2]*Maharishi University of Information Technology, Lucknow, India, Email Id- daljeetpalsingh1768@gmail.com, Orcid Id- 0009-0002-8391-7289*
[3]*JAIN (Deemed-to-be University), Karnataka, India, Email Id- p.raja@Jainuniversity.ac.in, Orcid Id- 0000-0002-4227-7011*
[4]*Chitkara University, Rajpura, Punjab, India, tannmay.gupta.orp@chitkara.edu.in, https://orcid.org/0009-0001-3147-5848*
[5]*Vivekananda Global University, Jaipur ravikant_pareek@vgu.ac.in, Orcid Id- 0000-0003-4981-2301*

Part 4 assesses the efficiency of the proposed method, and Part 5 concludes the paper.

## 2. Related Works

The paper [6] recent developments in computer vision methods for determining the state of civil infrastructure.The study explores the use of algorithms for computer vision in inspection applications to recognize structural elements, describe observable damage at both regional and worldwide sizes, and identify modifications compared to a reference image. The conclusion recognizes the advancements made using computer vision algorithms in assessing civil infrastructure while emphasizing the necessity for ongoing study and development.

The study [7] examined the variables affecting sharing of data in civil infrastructure planning and to determine the most important areas to focus on in order to encourage data sharing among civil engineers.Researchers and experts in the field of civil infrastructure were surveyed online for their perspectives.By highlighting the significance of cooperation across policy, commercial models, and technical solutions, the research offers a roadmap for boosting sharing of data in civil infrastructure engineering.

By deploying swarms of independent inspection robots to monitor the health of civil infrastructures, the study [8] increased resource efficiency without lowering damage detection performance. The article presents a method based on network pruning with Taylor expansion to effectively use instructed convolutional neural networks with deep learning for edge computing and integration into inspection robots.

The paper [9] suggested two deep learning-based crack segmentation and detection methods. The first method combines structured random forest edge detection (SRFED) and the faster region-based convolutional neural network (FRCNN). The integrated visualization capabilities give users a thorough understanding of the structures being investigated, which helps with infrastructure management and maintenance.

Article [10] created a smart, human-centered mixed reality (MR) foundation incorporated into a wearable hologram headset device for infrastructure assessment. The suggested approach involves integrating MR technology with attention-guided semi-supervised deep learning. The proposed smart MR foundation has an opportunity to revolutionize infrastructure inspection.

The study [11] used a reasonable infrastructure resilience strategy that considered the structural qualities of infrastructure networks and the sociodemographic traits of specific households. The findings emphasize the significance of an equitable resilience approach in infrastructure systems to properly prioritize investments and eliminate risk disparities for vulnerable populations during service disruptions.

Study [12] pinpointed the statistically important factors influencing how quickly emergency management operations can be restored after an earthquake. The researchers used an analysis of variance (ANOVA) technique to find the statistically relevant variables. In this instance, the researchers evaluated the effect of several variables on the restoration time using ANOVA. These findings highlight the significance of comprehending the built environment and local environmental factors for creating efficient post-earthquake emergency management plans.

Research [13] developed a convolutional neural network (CNN)-based fault classification system for CCTV inspection footage used to check the status of sewer pipeline systems. The findings of this study lay the groundwork for future investigations into the development of even more reliable models for assessing sewer pipeline networks.

Study [14] investigate using frequency-modulated continuous wave (FMCW) sensing, particularly K-band analysis, as a novel technique for non-invasive, non-contact, and non-destructive examination of subsurface materials in intricate multi-layer structures. The researchers used FMCW feeling in the K-band frequency region to analyze complicated multi-layer systems. The study's findings proved that FMCW analysis could successfully identify subterranean fault origins in civil infrastructure.

Article [15] evaluated the different ways that infrastructure contributes to cities' present levels of resilience and sustainability as well as the potential for improvement. The article will determine how resilient and sustainable infrastructure is by taking into account elements like social equality, resource efficiency, environmental impact, and flexibility to adapt to changing circumstances. The article concludes that communities can reduce the drawbacks of infrastructure while increasing its benefits by taking a proactive and all-encompassing strategy.

## 3. Proposed Method

In this paper, we suggest a Swarm-Intelligent Aquila Optimisation (SIAO) approach to evaluate the state of civil infrastructure. Figure 1 depicts the overview of methodology.

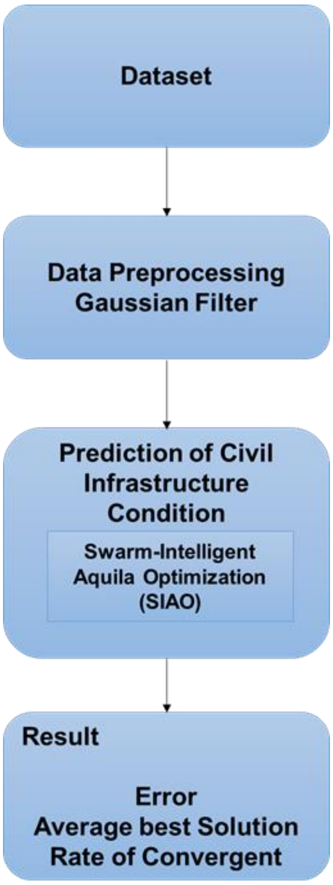


**Fig 1 :** Overview of proposed method

### 3.1 Dataset

This study provided the dataset, which consists of 436 images with a resolution of 430*400 pixels. The findings are derived from two main sources: laboratory tests on reinforced concrete columns and records of bridge damage following earthquakes. Images are scaled down to 215*200 pixels for processing performance.

### 3.2 Preprocessing

The acquired data is preprocessed using a Gaussian filter. Data preprocessing is transforming and cleaning raw data to prepare it for modeling and analysis. GF (Gaussian filter) effectively uses Gaussian mask kernels to improve and remove the noisy elements from the image. Civil Infrastructure usually has many different numbers of pixels. The Civil Infrastructure is separated into some combinations groups. One of those combinations applies the pixel group to a GF; the resulting pixel is an improved version of the original pixel and is substituted in the same location For example, for every pixel with intensity value$P_{xy}(1 \leq x \leq R, 1 \leq y \leq J)$ $for\ an \quad R * J$ Civil Infrastructure, the corresponding pixel of the noisy Civil Infrastructure u_xyis given as follows: Noise is modeled as additive white Gaussian noise (AWGN), where all the Civil Infrastructure pixels depart from their original

$$u_{xy} = P_{xy} + G_{xy} \tag{1}$$

Many Gaussian noise reduction approaches require understanding the standard deviation for measuring the level of distortion to establish the thresholds and the filtering window size, where every noise value $G_{xy}$ is derived from a zero-mean Gaussian distribution.

### 3.3 The Aquila Optimizer (AO)

The optimization procedure is completed in the Aquila Optimizer (AO) on a set of solutions ($W$), as indicated by Eq (2)

$$W = \begin{bmatrix} w_{1,1} & \cdots & w_{1,i} & w_{2,1} & \cdots & w_{2,i} & \cdots & \cdots & w_{j,i} & w_{1,Dim-1} & w_{1,Dim} & \cdots & w_{1,Dim} & \cdots & \cdots & \vdots \\ \vdots & \vdots & w_{M-1,1} & \cdots & w_{M-1,i} & w_{M,1} & \cdots & w_{M,i} & \vdots & \vdots \\ \cdots & w_{M-1,Dim} & w_{M,Dim-1} & w_{M,Dim} \end{bmatrix} \tag{2}$$

The decision values for these solutions range from the highest ($VA$) to the lowest ($KA$) in the Aquila Optimizer (AO). The optimal solution is selected after each cycle. Where $W$represents the chosen candidate solutions, R represents the total quantity of answers in $W$, and these solutions were produced using Eq (2),

$$W_{j,i} = rand \times (VA_i - KA_i) + KA_i, \tag{3}$$

Where a random value is called rand. Dim is the number of locations in the evaluated problem that have been used, $M$ is the number of potential solutions used, and $W_i$is the choice of the solution (3) (4). AO mathematical model the following presents the AO's mathematical representation.

$$i = 1,2,4,5, \ldots, M \tag{4}$$

$$i = 1,2,3,4,5, \ldots, Dim \tag{5}$$

The first component ($W_1$) is represented mathematically as stated in Eq (5).

$$W_1(s+1) = W_{best}(s) \times \left(1 - \frac{s}{S}\right) + (W_N(s) - W_{best}(s) * rand\ ) \tag{6}$$

Where the best answer is presented by $W_{best}(s)$, and $(\frac{1-s}{s})$ is a control search mechanism, and the mean value of the employed solutions, $WN(s)$, is found by Eq (6).

$$W_N(s) = \frac{1}{N}\sum_{j=1}^{M} W_j(s), \ \forall i = 1,2, \ldots, Dim \tag{7}$$

The used iteration and the maximum iteration are denoted by $s$ and $S$, respectively. The second component ($W_2$) is stated mathematically as indicated in Eq (7).

$$W_2(s+1) = W_{best}(s) \times levy\ (Dim) + W_Q(s) + (z - w) * rand \tag{8}$$

Where $W_N(s)$is a randomly chosen candidate solution and Levy($C$) is determined using Eq (8).

$$Levy\ (C) = t\ \times \frac{v \times \sigma}{|v|^{\frac{1}{\beta}}} \quad (9)$$

Where you and are arbitrary numbers, and s is a variable adjusted to 0.01. is determined by Eq (9).

$$\sigma = \left( \frac{\Gamma(1+\beta) \times sinf\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right) \quad (10)$$

During the search procedure, which is as follows, the spiral form in Equation is shown using $z$ and $w$. (10),

$$z = q\ \times cos\ cos\ (\theta) \quad (11)$$

$$w = q \times sin\ (\theta) \quad (12)$$

$$q = q_1 + V \times C_1 \quad (13)$$

$$\theta = -x\ \times C_1 + \theta_1 \quad (14)$$

Where it is changed to 1.5. $q_1$is a value between $C_1$has a value between [1 Dim] and is fixed at [1 20], $U$ is fixed at 0.00565, and [1 Dim] at 0.005. The original paper serves as the source for all parameter values. The original paper is the source for all parameter values (11) (12) (13).The third component ($W_3$) is mathematically represented as stated in Eq (14),

$$W_3(s+1) = \left(W_{best}\ (s) - W_N(s)\right) \times \alpha - rand + \left((VA - KA) \times rand + KA\right) \times \delta \quad (15)$$

Where parameters are fixed at 0.1 and respectively. The fourth component ($W_4$) is represented mathematically, as provided in Eq (15).

$$W_4(s+1) = RE\ \times W_{best}\ (s) - (H_1 \times W(s) \times rand) - H_2 \times Levy\ (C) + rand\ \times H_1 \quad (16)$$

Where the current resolution is $W_{(S)}$, $H_1$and $H_2$are derived by Eqs. (16, 17), and $RF$, the quality function found in Eq. controls the search processes eq (18).

$$RE(s) = s^{\left(\frac{2\ \times rand\ () - 1}{(1-S)^2}\right)} \quad (17)$$

$$H_1 = 2\ \times rand\ () - 1 \quad (18)$$

$$H_2 = 2\ \times \left(1 - \frac{s}{S}\right) \quad (19)$$

### 3.4 Particle Swarm Optimizer (PSO)

The optimum solution was discovered using the Particle Swarm Optimizer (PSO), updated after each iteration. PSO updates the candidate solutions using two basic methods: position update, as in Eq., and velocity, as in Eq. The best local solution is L BI, and the best global option is G BI. With Eq., the inertia weight value is computed by taking the maximum and minimum values, usually fixed at 0.2 and 0.9 (19) (20) (21).

$$W(s+1) = W_{ji} + U_{ji} \quad (20)$$

$$U_{j,i} = x * \times U_{ji} + d_1 \times rand_1 \times \left(KA_1 - w_{j,i}\right) + d_2 \times rand_2 \times \left(HA_1 - w_{j,i}\right) \quad (21)$$

$$x = x_{max} - x_{min} \times \left(\frac{J_{max} - J}{J_{max}}\right) + x_{max} \quad (22)$$

### 3.6 Swarm-Intelligent Aquila Optimization (SIAO)

The Aquila Optimizer is a full optimization program incorporating Particle Swarm Optimization (PSO) concepts and other optimization methods. PSO is a population-based stochastic optimization method that draws inspiration from the social behavior of fish schools and bird flocks. It replicates the motion of particles in a search space, with each particle modifying its position in response to its individual knowledge and the collective wisdom of the swarm.

To boost the algorithm's effectiveness and resilience, the hybrid version of Aquila Optimizer employs one or more additional optimization techniques. Different strategies may be used depending on the precise issue being resolved and the desired optimization objectives. As an illustration, the hybridization might incorporate PSO with evolutionary algorithms, simulated annealing, or local search techniques.

The hybrid Aquila Optimizer explores and utilizes the search space more thoroughly by integrating the benefits of various optimization approaches. While the extra strategies help improve local exploitation and convergence to optimal solutions, the PSO component enables effective global exploration. The Aquila Optimizer can handle various complex optimization issues thanks to the synergy between many methods, which enhances the entire optimization process .

## 4. Result

This section evaluates the efficacy of the recommended and existing approaches. The parameter is an error, the average best solution, and the convergence rate. Dolphin echolocation (DE) [11] and Particle Swarm Optimizer (PSO) [12] are the existing methods

The potential that the parameters used to create the model are inaccurate even while the model is correct is known as parameter error. First, this possibility exists due to insufficient data to predict the parameters. The error value is decreased our proposed method. Figure 2 and table 1 depicts the error outcome. While comparing with exisiting method our proposed method is lower. it demonstrates thart our proposed method is effective in predicting the civil infrastructure condition.

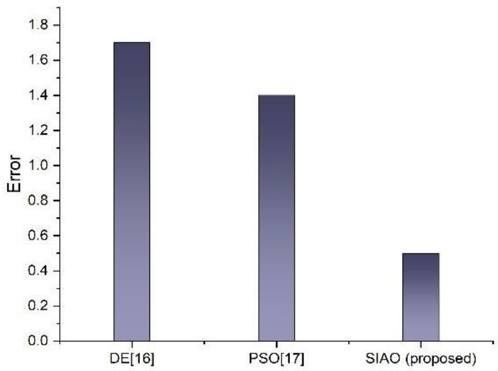


**Fig 2:** Outcome of Error

**Table 1**: Value Of Error

| Methods | Values |
|---|---|
| DE[16] | 1.7 |
| PSO[17] | 1.4 |
| SIAO (proposed) | 0.5 |

The phrase "average best solution parameter" does not have a widely accepted or established definition in the optimization field. Figure 3 and table 2 depicts the intermediate best solution. While comparing with exisiting method our proposed method is greater. it demonstrates thart our proposed method is superior for predicting the civil infrastructure condition.

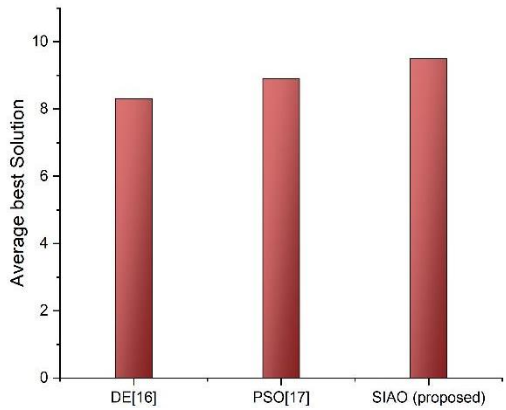


**Fig 3**: Outcome of average best solution

**Table 2:** Value of average best solution

| Methods | Value |
|---|---|
| DE[16] | 8.3 |
| PSO[17] | 8.9 |
| SIAO (proposed) | 9.5 |

The phrase "rate of convergence" describes how rapidly an iterative process or sequence gets close to a limit or the desired outcome. It is frequently used in mathematics and numerical analysis to gauge how quickly a specific approach or algorithm leads to the intended or accurate outcome. While comparing with exisiting method our proposed method is greater. it demonstrates thart our proposed method is better in predicting the civil infrastructure condition.

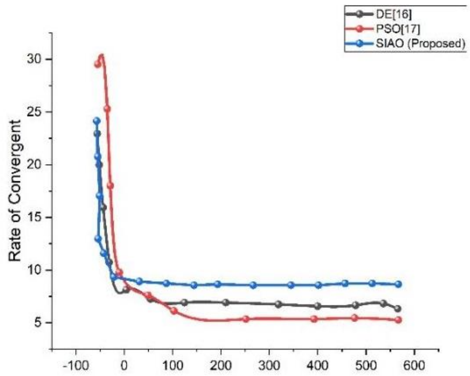


**Fig 4:** Outcome of convergent rate

## 5. Conclusion

A promising way to assess civil infrastructure conditions is the Swarm-Intelligent Aquila Optimization (SIAO) method. This approach outperforms conventional approaches in terms of efficacy, accuracy, and dependability by utilizing the collective intelligence of a simulated swarm. The effective use of SIAO in monitoring structures using concrete image datasets suggests that it has the potential to change the field of building engineering and enable proactive control and maintenance of crucial infrastructure assets. The Swarm-Intelligent Aquila Optimization (SIAO) method's dependency on precise and comprehensive concrete image datasets is one of its drawbacks [18]. Expanding the SIAO method's applicability to other types of civil infrastructure outside buildings, like bridges or dams, could be the subject of future research and development. [19]

## References


[1] Jayawickrema, U.M.N., Herath, H.M.C.M., Hettiarachchi, N.K., Sooriyaarachchi, H.P. and Epaarachchi, J.A., 2022. Fibre-optic sensor and deep learning-based structural health monitoring systems for civil structures: A review. Measurement, p.111543.

[2] Silva, M., Martinez, B., Figueiredo, E., Costa, J.C., Yang, Y. and Mascareñas, D., 2020. Nonnegative matrix factorization-based blind source separation for full-field and high-resolution modal identification from video. Journal of Sound and Vibration, 487, p.115586.

[3] Misra, Y., Krishnaveni, K. and Rajasekaran, A.S.,

2022. Implementation of NLOS based FPGA for distance estimation of elderly using indoor wireless sensor networks. Materials Today: Proceedings, 57, pp.2299-2306.

[4] Das, S. and Saha, P., 2021. Performance of swarm intelligence based chaotic meta-heuristic algorithms in civil structural health monitoring. Measurement, 169, p.108533.

[5] Guha, R., Chatterjee, B., Khalid Hassan, S.K., Ahmed, S., Bhattacharyya, T. and Sarkar, R., 2022. Py_fs: a python package for feature selection using meta-heuristic optimization algorithms. In Computational Intelligence in Pattern Recognition: Proceedings of CIPR 2021 (pp. 495-504). Springer Singapore.

[6] Spencer Jr, B.F., Hoskere, V. and Narazaki, Y., 2019. Advances in computer vision-based civil infrastructure inspection and monitoring. Engineering, 5(2), pp.199-222.

[7] Wang, Y., Tang, P., Liu, K., Cai, J., Ren, R., Lin, J.J., Cai, H., Zhang, J., El-Gohary, N., Berges, M. and Golparvar Fard, M., 2023. Characterizing data sharing in civil infrastructure engineering: Current practice, future vision, barriers, and promotion strategies. Journal of Computing in Civil Engineering, 37(2), p.04023001.

[8] Wu, R.T., Singla, A., Jahanshahi, M.R., Bertino, E., Ko, B.J. and Verma, D., 2019. Pruning deep convolutional neural networks for efficient edge computing in the condition assessment of infrastructures. Computer-Aided Civil and Infrastructure Engineering, 34(9), pp.774-789.

[9] Kalfarisi, R., Wu, Z.Y. and Soh, K., 2020. Crack detection and segmentation using deep learning with a 3D reality mesh model for quantitative assessment and integrated visualization. Journal of Computing in Civil Engineering, 34(3), p.04020010.

[10] Karaaslan, E., Bagci, U. and Catbas, F.N., 2019. Artificial intelligence-assisted infrastructure assessment using mixed reality systems. Transportation Research Record, 2673(12), pp.413-424.

[11] Coleman, N., Esmalian, A. and Mostafavi, A., 2020. Equitable resilience in infrastructure systems: an empirical assessment of disparities in hardship experiences of vulnerable populations during service disruptions. Natural Hazards Review, 21(4), p.04020034.

[12] Fraioli, G., Gosavi, A. and Sneed, L.H., 2020. Strategic implications for civil infrastructure and logistical support systems in post-earthquake disaster management: the case of St. Louis. IEEE Engineering Management Review, 49(1), pp.165-173.

[13] Hassan, S.I., Dang, L.M., Mehmood, I., Im, S., Choi, C., Kang, J., Park, Y.S. and Moon, H., 2019. Underground sewer pipe condition assessment based on convolutional neural networks. Automation in Construction, 106, p.102849.

[14] Mitchell, D., Blanche, J. and Flynn, D., 2020, November. An evaluation of millimeter-wave radar sensing for civil infrastructure. In 2020 11th IEEE Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON) (pp. 0216-0222). IEEE.

[15] Neuman, M., 2020. Infrastructure is key to making cities sustainable—sustainability, 12(20), p.8308.

[16] Qiu, Y., Wang, Z., Pan, J., Hu, F., Sharma, S. and Deifalla, A.F., 2022. Optimal Design of Semirigid Connection Steel Frame with Steel Plate Shear Walls Using Dolphin Echolocation Algorithm. Buildings, 12(10), p.1735.

[17] Peckens, C.A.; Alsgaard, A.; Fogg, C.; Ngoma, M.C.; Voskuil, C. Utilizing the Particle Swarm Optimization Algorithm for Determining Control Parameters for Civil Structures Subject to Seismic Excitation. Algorithms 2021, 14, 292.

[18] Padave, P. R. & Reddy, J. S. (2022). Effectiveness of Swarm Robotics in Coordination of Multiple Robots as a System That Consists of Large Numbers of Mostly Simple Physical Robots. Technoarete Transactions on Industrial Robotics and Automation Systems (TTIRAS), 2(3), 9–10.

[19] Jaya Rubi., & Geraldin B. Dela Cruz. (2022). Intelligent Marketing: Integrating Artificial Intelligence Principles and Techniques into the Advertising and Marketing Process. Technoarete Transactions on Advances in Computer Applications (TTACA), 1(3), 1-7.