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Optimized wireless Sensor Nodes Placement with multi-Objective Hybrid Optimization Algorithm

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Abstract: The article presents the optimal sensor node placement problem in Structural Health Monitoring (SHM) application based on an optimized Wireless sensor network (WSN). The sensor node placement problem is formulated in multi-objective form by considering the energy consumption, sensitivity area and network lifetime. We developed a hybrid optimization algorithm by a combination of Chaotic Particle Swarm Optimization (CPSO) with Gravitational Search Algorithm (GSA) to provide optimal sensor node placement in WSN based SHM system. The optimal solution is achieved in the Pareto environment case, which makes the algorithm multi-objective. The conflicting nature of these objectives makes them best suitable for multi-objective optimization. A Chaotic response is used to update the PSO algorithm and exploitation phase of the PSO update as per the GSA. The Multi-Objective Chaotic Particle Swarm Optimization with Gravitation Search Algorithm (MOCPSOGSA) has attained the minimum value of a highly non –linear objective function with a faster convergence response. The maximum value of residual energy, cover area and network lifetime are achieved with the multi-objective CPSOGSA algorithm. The outcomes of the proposed MOCPSOGSA algorithm are compared with the PSO algorithm. The MOCPSOGSA achieves superior performance for GNTV tower china health monitoring. The safety and economic concern of SHM tasks are better achieved in the case of the proposed MOCPSOGSA optimized WSN network.

Keywords: SHM, Multi-objective, PSO, GSA, Chaotic mapping, GNTV tower, WSN, Sensor node deployment, etc.

1. Introduction

Large-scale civil infrastructure like bridges, airport, long-span structure, railway structure and oil pipeline are indispensable for humans and their daily lives. The ageing effects, environmental load, corrosion effect and fatigue on the building structure can damage them that lead to accidents. Efficient operation and safety are providing structure with the monitoring and diagnosis of the faults. The structural damages are timely detecting by applying the structural health management system. The structural health monitoring (SHM) term is derived from the aerospace field to monitor the structural load. The concept of SHM is gradually enriched with the enlargement design and complication. It involves structural damage detection, building life prediction and location of the damage.

The damage detection and localization tasks are performed in a building by Structural Health Monitoring (SHM). The key purpose of SHM is to minimize economic losses and prevent catastrophic failures and human lives. The wireless sensor network (WSN) is a low-cost solution in the SHM for existing and newly constructed buildings. Presently the interest in wireless sensor network (WSN) is enhanced in both industry and academy applications. This is due to the monitoring system characteristics and minimized deployment and repairing costs of an environment. With the advancement of new inventions, various practical applications are rolled out. The specific applications are smart building, smart grid and smart farming. In WSN, several sensors are placed in the network that captures information, and a single node collected all data. Due to the few interesting features of sensors enhance the utilization of WSN technology. The sensors are small power autonomous, cheap, and wireless that can capture several types of measurement in the same device. The deployment cost of the sensor network is less due to the absence of wires. The deployment of wired base technology is expensive and wireless network can overcome the drawback of higher cost. State of the art, several researchers have shown their interest in SHM by using optimal sensor node placement.

Due to the resource-constrained in WSN, the SHM raises few challenges like significant data generation, synchronization and optimal routing. For smart building and critical infrastructure like bridges, WSN is the best solution. All the stable and long-lasting building structure life can be monitored by the WSN based SHM [1]. The safety of the buildings is enhanced with the WSN based SHM and awareness about the forthcoming risk. The optimal placement of sensor nodes is a major issue of the WSN based SHM system. The sensor node consumes higher energy with the limited connectivity information that minimizes the information quality. The sensor node placement task also suffers from connectivity and coverage loss due to more miniature sensor node utilization. The minimum sensor node deployment can reduce the economic losses, as mentioned in [2].

The sensor nodes used in the WSN are battery-powered have limited energy. The recharging and battery replacing process are not possible for the sensor node placement due to its costly nature. The active nodes present in the network share the received information with neighbour nodes and relays nodes. The sensor node deployment in the network is preplanned or can be placed randomly in the network. The nodes available in the sensor network is complete with the other nodes for shared frequency for data transmission task. The performance of the wireless network is affected by several attacks like coverage hole and spectrum attacks. In [3], a primary user emulation (PUE) attack impacts the WSN performance for measuring the vibration of home and buildings. The sensor nodes are used to monitor the vibrations in the building structure. The vibrations are caused by the earthquake, WSN traffic, strong winds. A sensor node deployment scheme based on the innovative minimally invasive technology is presented to monitor the structural behaviour under normal conditions [4].

The early warning of an earthquake by using innovative 5G architecture based SHM system to detect the seismic event and forwarded the message about the event detection to the other buildings that the event may damage. The SHM based on WSN is also surveyed in [5,14, and 22] and studied the management based scheme also. Different materials like reinforced concrete (RC), concrete Elements (CE), and masonry structure are tested with the WSN based SHM [6]. The environmental arrangement is settled based on the PZT sensors. The WSN performance is affected by the big data generation that should be minimized. The BigReduce technique is proposed for cloud health monitoring that improves monitoring quality and minimizes big data [7]. The fault tolerance issues are arriving in the WSN based SHM that affect the performance of damage detection.

A MidSHM algorithm is proposed to minimize fault tolerance for 3D urban terrain scenario [9 and 10]. The performance of WSN based SHM is enhanced by considering multi-objective problems like coverage, connectivity quality, and reliability. A sensor node placement for civil, structural health monitoring is studied in [13]. The proposed SPEM scheme achieves the critical placement of quality information. The SPEM scheme is evaluated with the existing SHM of Ting Kau Bridge. The Guangzhou New TV Tower [13, 21] is tested by the proposed scheme, which provided helpful improvement. The deployment of a wireless sensor at the strategic location of a building structure provided effective health monitoring. The WSN based fault tolerance scheme [15] is presented for the SHM, and a specific degree of fault tolerance attained. The WSN faults are also repaired by the Dependable SHM scheme [16, 18].

The Depend SHM can detect the fault of sensors automatically and repaired them, which improved the health monitoring of a city building. A three-phase sensor placement approach (TPSP) is proposed for the SHM [17]. TPSP approach provided the optimal placement of sensor nodes, improved communication efficiency, reliability and minimized the failures of

WSN during SHM. Fault tolerance, low consumption cost, and lifetime are improved by sensor fault detection [18]. A wireless vibration sensor network (WVSNs) is proposed for the SHM in [19]. The FFT under QAM is applied to the vibration data acquisition stage, and then the Goertzel algorithm [19] is used to reduce the sensor data in the transmission case. The large data of SHM is also reduced by the theory of probability approach [25]. The decision-making algorithm is proposed to reduce the intensive data communication on the sensor nodes.

We go through several studies and analyze that the sensor node's optimal location is mandatory for the efficient SHM task. The sensor node placement in a wireless network depends on the energy consumption, the distance among sensor nodes and reliable behaviour. A hybrid algorithm like CPSO (Chaotic PSO) [11,12] shows optimal performance in linear optimization. The meta-heuristic techniques are used for optimal sensor node placement but time-consuming. The lifetime of a WSN is maximizing by the optimal solution of SHM using optimal power and path selection with and without energy harvesting [20]. The optimization problem's complexity is minimized by the suboptimal routing (Branch and Bound Algorithm) and heuristic routing algorithm (Genetic Algorithm). Fe optimization algorithm like FireFly Algorithm (FFA) [24], greedy search algorithm [28] and several previous optimization algorithms are considered for the single and multi-objective problems. The position of relays were optimized using moth flame optimizer (MFO), interior search algorithm (ISA), bat algorithm (BA) [30]. The authors discussed the issue for coverage hole-free nodes deployment by modifying Prim's algorithm to select those vertices in the network which don't create holes [31].

The node energy, sensitivity, reliability and node lifetime are considered key terms for the sensor node placement in the SHM. In previous papers, the multi-objective problem is not considered for the SHM purpose while implementing the optimization task. A multi-objective problem can be designed for the optimal sensor node placement in the WSN based SHM.

The challenges like high energy consumption, reliability, and cost are considered for the optimal sensor node placement in the network. The WSN based SHM performance is enhanced by Pareto optimal solution. We consider a multi-objective problem for optimal configuration of WSN in SHM application. A hybrid multi-objective optimization algorithm is developed by combining Chaotic Mapped (CPSO) and gravitational search algorithm (GSA) to monitor damage condition for the Guangzhou New TV Tower structure. The proposed solution is tested with the Pareto condition and select the optimal nodes from the neighbor's nodes to improve the performance of the WSN.

Further in this paper, section II has the network model assumptions followed by the 3rd section Multi-objective CPSOGSA brief. The proposed work is discussed in the fourth section, and results are analyzed in the fifth section. The concluded arguments are presented in final section VI.

2. Network Model and Assumptions

Recently, building health monitoring is an essential requirement of the world. Few traditional methods like visual inspection and measurements are used for monitoring the health of the building structure. The damages are manually monitored with the traditional structural health monitoring algorithms. The structural health monitoring task is depending on the sensor node placement in a wireless sensor network. The realistic environment monitoring enhances the monitoring task efficiency. The WSN based SHM model can automatically monitor the condition of the building. In this work, we developed a WSN based SHM model to identify the threat of damages to the buildings. A WSN model is described in this section with the general assumptions and specific details of network lifetime, energy consumption and sensitivity area. The multiple objectives have enhanced the performance of realistic model scenario, so we consider three objective functions to perform optimization task simultaneously. The mathematical expression for the WSN model is described in this section.

2.1 Energy consumption

The energy model used in [32] is considered to simulate the execution time's energy cost. The sensors are energy-limited devices that cause a higher cost of energy generation and storage. The mathematical expression for the energy cost is derived by a sensor $i = (x, y) \in S_s(t)$ where $x \in [0, d_x]$ and $y \in [0, d_y]$ sends several packets to $P_i(t)$ at time $t > 0$ denoted as;

$$P_i(t) = 1 + R_{P_i}(t) \quad (1)$$

The number of packets captured by i is considered for the formulation. A packet per instant time and number of packets deployed by the sensor i, $R_{P_i}(t)$ due to the multi-hop routing protocol and computed as;

$$R_{P_i}(t) = \sum_{j \in \{S_s(t)-i\}} Z_{j,i}^{c}(t) \tag{2}$$

If $i \in S_s(t)$ is the minimum path among $j \in S_s(t)$ and sink node c at $t > 0$, then value of $Z_{j,i}^{c}(t)$ is 1 otherwise 0. The energy cost for the sensor i at time instant t is denoted as $E_{e_i}(t)$ and computed as;

$$E_{e_i}(t) = P_i(t)\beta\, amp\, k\, (\|i - w_i^c(t)\|_d)^{\alpha} \tag{3}$$

In equation 3 $\|.\|_d$ is the Euclidean distance among two points, transmission quality parameter is known as $\beta > 0$, $amp > 0$ energy cost per bit of power amplifier and information packets size in bits is represented by $k > 0$. The minimum path between sensor $i \in S_s(t)$ and sink node at time $t > 0$ is provided by the variable $w_i^c(t)$, the path loss exponent $\alpha \in [2,4]$. An energy charge of sensor i at time instant t is estimated as;

$$E_{C_i}(t) = \begin{cases} E_{C_i}(t) - E_{e_i}(t) & if\ t > 0 \\ iec & if\ t = 0 \end{cases} \tag{4}$$

The initial energy charge of the sensors is denoted by the iec for $iec > 0$, so the sensor is out of energy in case of $E_{C_i}(t) = 0$.

2.2 Sensitivity area

A sensor covers a circumference of radius r_s and area πr_s^2. At time t the WSN sensitivity area is estimated as the union of the areas of active sensors time t with a path to the sink node $S_s(t)$. Equation 5 denotes the sensitivity are $A(t)$ provided by a WSN at time $t > 0$

$$A(t) = \frac{1}{\check{d}_p(t)} \sum_{p \in \check{D}_p(t)} a_p(t) \tag{5}$$

Here $a_p(t)$ is the indicator function defined as;

$$a_p(t) = \begin{cases} 1 & if\ \exists i \in S_s(t): \|p - i\|_d < r_s \\ 0 & otherwise \end{cases} \tag{6}$$

If there is an active sensor i then $a_p(t) = 1$ and distance is lower than the r_s from the demand point p.

The number of demand points at the time $t > 0$ is estimated as;

$$\check{d}_p(t) = \frac{d_x d_y}{d_{pn}} \tag{7}$$

2.3 Network lifetime

It is defined as the number of periods over which the network provides the information is utilized for an application. The network lifetime is denoted by t_n and threshold sensitivity area is used for the formulation;

$$t_n = \|\{t > 1 \in \tau: A(t) > co_{th}\}\| \text{ for } \tau = 1,2,3,.. \tag{8}$$

Here the set of periods is τ, and cardinal of a set is denoted by $\|.\|$.

2.4 Optimization problem

The above estimated three terms are energy consumption by sensors, sensitivity area and network lifetime. The optimal placement of sensor nodes is done by minimizing the energy consumption and maximize the sensitivity area and network lifetime. The three objective functions are formed and optimized based on the Multi-objective concept of optimization. Suppose the energy consumption is denoted as

$$f_1 = E_{C_i}(t) \tag{9}$$

The sensitivity area over the entire network is defined as;

$$f_2 = \frac{1}{t_n} \sum_{t=1}^{t_n} A(t) \tag{10}$$

The network lifetime depends on the distance among the sensor nodes and energy consumption, so the objective function for network lifetime is considered as;

$$f_3 = \frac{1}{t_n} \sum_{t=1}^{t_n} \sum_{i \in S_s(t)} \frac{E_{e_i}(t)}{S_s(t)} \tag{11}$$

The three objective optimization problem is designed by maintaining the limits of the same constraints,

$$\min f_1 . \max f_2 . \max f_3 \tag{12}$$

The problem is in the form of a multi-objective, and the solution is to find out by hybrid optimization algorithm in multi-objective form. The developed hybrid multi-objective optimization algorithm is explained in the next section.

3. Proposed Solution

In this work, we proposed a multi-objective solution to the SHM problem based by optimizing the sensors node placement in WSN. Based on the objective function, the optimization algorithms are divided into two different categories Single Objective Optimization (SOO) and Multi-Objective Optimization (MOO). A MOO algorithm provides an optimal solution to complex real-world problems. The MOO can achieve the set of trade-off solutions in a single simulation run. Recently the MOO algorithm is used to solve different, distinct varied optimization problems. In the MOO algorithm, the multiple issues are not combining and restore into a single objective. The optimization algorithm implementation cost is increased with the combination of numerous objective functions into single objectives. For a multi-objective problem, a single objective optimization algorithm generates an available solution; after that next objective solution is provided via an update of the weights of the algorithm. The MOO can generate a complete set of Pareto front solutions in a single run that provides optimal choice among the two solutions. The basic concept of multi-objective optimization is defined as;

$$minimize\ f(x) = [f_1(x), f_2(x), \ldots. f_k(x)] \quad (13)$$

Subjected to;

$$g_i(x) \leq 0, \qquad i = 1, 2, 3, \ldots\ldots, m \quad (14)$$

$$h_i(x) = 0 \qquad i = 1, 2, 3, \ldots., p \quad (15)$$

Here the vector of decision variables is denoted by $= [x_1, x_2, \ldots\ldots, x_n]^T$, $f_i: \mathbb{R}^n \to \mathbb{R}$ is the objective function, and constraints limits are denoted by $g_i(x)$and $h_i(x): \mathbb{R}^n \to \mathbb{R}$.

- The two given vectors $x, y \in \mathbb{R}^k$ we can say that $x \leq y$, if $x_i \leq y_i$ for $i = 1, 2, 3, \ldots, k$ means $x\ dominants\ y\ (x \prec y)$ if $x \leq y$ and $x = y$.
- A vector is a decision variable $x^* \in \mathcal{F} \subset \mathbb{R}^n$ ($\mathcal{F}$ is the feasible region) is Pareto optimal if it is non dominated to the $\mathcal{F}$.
- The Pareto optimal set can be defined as $P^* = \{x \in \mathcal{F} | x \text{ is Pareto optimal}\}$
- The Pareto front defined as; $P\mathcal{F}^* = \{f(x) \in \mathbb{R}^k | x \in P^*\}$
- All the decision variables must satisfy the condition from 13 to 15, and Pareto optimal solution is determined from the set $\mathcal{F}$.

In this work, we hybrid the Chaotic PSO algorithm with the GSA algorithm and tuned the multi-objective problem. The cellular automata optimization algorithm basic concept is explained below;

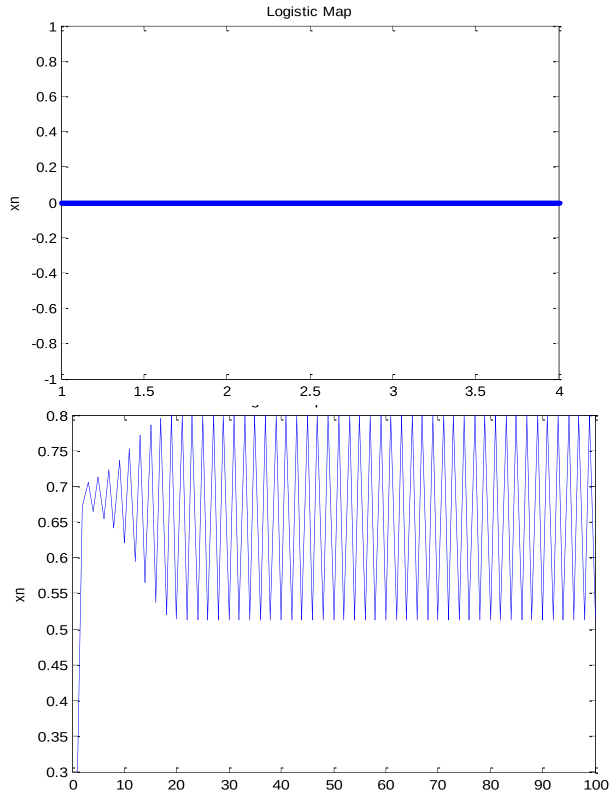
3.1 Chaotic mapping

Chaotic maps generate the pseudo-random numbers, which are non-linear and ergodic. Several chaotic maps like tent map, logistic map, Tchebychev map etc., are available, but logistic map provides the randomness near the solution. It is a linear mapping with variable $x_n = rx_n(1 - x_n), n = 0,1,2,3$ ..... The r is a system parameter $(0,4] and x_n \epsilon [0,1]$. The logistic mapping shows different behaviour for different values of r.

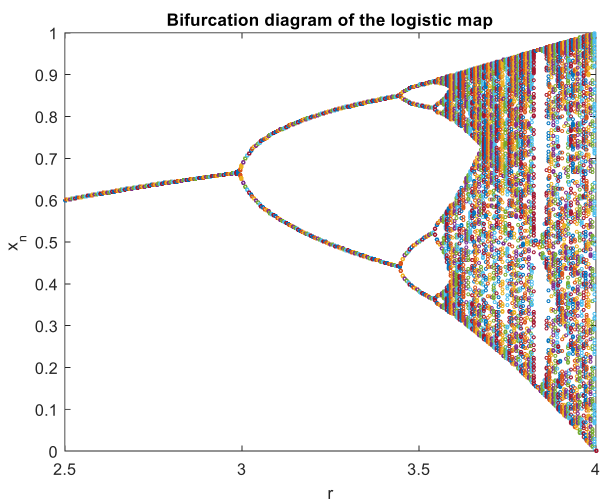
The initialization response of swarms' population with $r \in (0,4]$ is listed in table 1. The logistic map failed to converge for $r > 4$ as x_n Leaves the interval of 0 and 1. Fig. 1 shows the stationary, periodic and complete bifurcation diagram for the logistic map. Fig. 3(a) and 3(b) shows the behaviour of logistic mapping if the system parameter r is less than 1 and $3 \leq r < 1 + \sqrt{6}$ respectively. For $0 \leq r < 1$, the swarm particles can't explore the area for foraging and die prematurely. Conclusively, redundant sensor nodes won't be able to heal the holes. The non-diminishing oscillatory behavior (fig. 1(b)) also doesn't give any converging solution for redundant nodes' optimal locations. The chaotic behavior starts beyond 3.56994, and fig. 1(c) shows the logistic mapping for a complete range of $r \in (0,4]$. The area between $r \in (3.54409,4]$is the stable oscillations area, and convergence in optimization can be achieved in this area. The solid lines in fig. 3(c) point to the stable solution.

Table 1**:** Different behaviors of Logistic map for $r \in (0,4]$

Sr. No.	**Value of r**	**Response**
1	$0 \le r < 1$	The solution terminates prematurely very soon irrespective of the initial population
2	$1 \le r < 2$	The solution will approach towards $\frac{r-1}{r}$,
3	$2 \le r < 3$	Solution approaches towards $\frac{r-1}{r}$again but oscillates around that value for some time and converges linearly.
4	$3 \le r < 1+\sqrt{6}$	Solution oscillates permanently between two fixed values and stuck in a non-decreasing solution.
5	$1+\sqrt{6} \le r < 3.54409$	In this range, the solution takes permanent perturbation between four values
6	$r > 3.54409$	At this, oscillations take for 8 values, then 16,32 etc.
7	$r = 3.56994$	This onset value and beyond this chaotic behavior starts. No more finite oscillations are visible. Large searching space can be exploited with slight variation in the initial populations.



(a): for $r = 0.5$ (b) for $r = 3.2$



(c) for $r \in (0,4]$

Fig. 1**:** Stationary, periodic and bifurcation behavior of logistic mapping

3.2 Particle Swarm Optimization

Multi-objective optimization is a challenging task due to the simultaneous execution of several complex objectives with Pareto optimal sense. The particle swarm optimization (PSO) algorithm is easy to implement and has a high convergence speed. Due to these advantages, we consider PSO in a multi-objective optimization environment. It is inspired by birds' nature flock and provides optimal outcomes in terms of the stochastic search domain.

A particle swarm optimization algorithm is inspired by bird flocking behaviour. The number of a particle moving in the search space provides an optimal solution. The two key parameters of PSO are particle velocity and position, which are updated as

$$V_i^{t+1} = V_i^t + c_1.r_1(p_i^t - X_i^t) + c_2.r_2(p_g^t - X_i^t) \quad (16)$$

$$X_i^{K+1} = X_i^k + V_i^{K+1} \quad (17)$$

Here V_i^{K+1} is the velocity of particle-based on local best and global best value, $r_1 and\ nr_2$ are the selected random numbers, $c_1, c_2\ and\ c_3$ are the three constant values,X_i^k is the initial position of search agents, and X_i^{K+1} is the position update after velocity. We use the concept of single objective PSO to solve the multi-objective problem solution, so PSO has been modified with the Pareto Optimal solution. The convergence of the Pareto front problem or non-dominated solution problem and provide a solution against them. The actual PSO provides several non-dominated solutions in a single run against the Pareto Front set. The velocity and position of each particle are updated in each iteration. The real constants values are represented by$c_1\ and c_2$, and $r_1 and\ r_2$are the random numbers lie between 0 and 1. The best position of the particle provides the best solution for the fitness function. The leaders are equipped with particles in the case of the Multi-objective PSO algorithm. In MOPSO, the Pareto optimal test provides a global optimum solution to the objective functions [21]. The Pareto ranking scheme can handle the multi-objective problem efficiently. An external repository contains an archive controller and grid for is storing the previous best non-dominated solutions of the particle. The archive controller performs two main functions addition and deletion of the non-dominated solutions.

For multi-objective problems, a Pareto ranking scheme is added to the PSO algorithm. The main difference among the single and multi-objective optimization problems is that two solutions are compared in single-objective optimization, and all non-dominated solutions compared with each other. A solution is said to be dominated if $\forall_i \in \{1, 2, \dots, K\}$, $f_i(\vec{\boldsymbol{u}}) < f_i(\vec{\boldsymbol{v}})$. A decision vector $\vec{\boldsymbol{u}}$is non-dominate $\vec{\boldsymbol{v}}$ if and only if $\forall_i \in \{1, 2, \dots, K\}$, $f_i(\vec{\boldsymbol{u}}) \leq f_i(\vec{\boldsymbol{v}})$and $\exists i \in \{1, 2, \dots, K\}$, $f_i(\vec{\boldsymbol{u}}) < f_i(\vec{\boldsymbol{v}})$**.**

The Pareto ranking scheme is integrated into the PSO for the solution of multi-objective problems. In a single-objective optimization problem, the two solutions can be compared, but in multi-objective problems, all the solutions could not be compared completely. For multi-objective problem, a decision vector $\vec{\boldsymbol{u}} = (u_1, u_2, u_3, \dots, u_D)$ is said to be dominated $\vec{\boldsymbol{v}} = (v_1, v_2, v_3, \dots, v_D)$ if and only if $\forall_i \in \{1, 2, \dots, K\}$, $f_i(\vec{\boldsymbol{u}}) < f_i(\vec{\boldsymbol{v}})$. A decision vector $\vec{\boldsymbol{u}}$is non-dominate $\vec{\boldsymbol{v}}$ if and only if $\forall_i \in \{1, 2, \dots, K\}$, $f_i(\vec{\boldsymbol{u}}) \leq f_i(\vec{\boldsymbol{v}})$and $\exists i \in \{1, 2, \dots, K\}$, $f_i(\vec{\boldsymbol{u}}) < f_i(\vec{\boldsymbol{v}})$**.** A solution has superior performance in all criteria dominant to the other solution. If the other member dominates no member of a decision vector set, the vector set is known as the non-dominated set. The improvement of one objective could only attain at the expense of other objectives in the non-dominance case. The pseudo-code of the MOPSO algorithm is listed in algorithm 1.

Algorithm 1: Pseudocode MOPSO algorithm

```
Initialize Swarm
Initialize non dominated solution in the archive
Non dominated solution
Iteration start
While iteration< maximum iteration
For each particle
        Select non dominated particle
        Update the best position of swarm
        Calculate the best fitness value of the objective function
        Update the global best solution
End
Update the global best value in external achieve
      Find the non dominated optimal solution
      Iteration=iteration+1
End While
Store the results in external achieve
End
```

3.3 Hybrid MOCPSO

The hybrid of optimization has several approaches, as discussed in [30]. We have made the PSO, chaotic mapping and GSA as low level, co-evolutionary and heterogeneous hybrid methods. It is low level, and co-evolutionary as all the three approaches are combined into one and execute in parallel inside an algorithm instead of cascading of algorithms. Since these three methods are not the same in nature, so a proposed hybrid solution is heterogeneous. In our approach, PSO is used for the exploration phase, while GSA's strength of converging maturely is utilized at the exploitation phase. The chaotic mapping introduces the pseudo randomness and perturbation at two levels: for the initial positions of swarms and to update the gravitational constant in GSA. The hybridization process is depicted in fig. 2. Since the initial swarms in PSO are chaotically generated by the logistic mapping, the chaos variable x_i^j $, i = 1,2 \dots N$ can be mapped into the searching space as

$$P_i^j = x_i^j \left(P_{max,j} - P_{min,j}\right) + P_{min,j} \tag{18}$$

Here $j = 1,2,..D$ for searching space dimension.

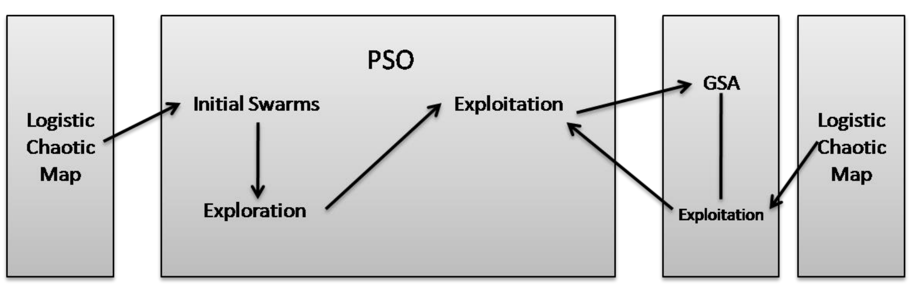


Fig. 2: Low-level hybrid process of PSO, chaotic mapping and GSA

In coverage holes healing problem, we have a fixed number of redundant nodes V_d And the objective is to deploy them to minimize the hole area, as discussed in the previous section. In actual we need to find the abscissa and ordinates of V_d. This fitness value is compared to the previous local best value, and the winner has to take part again in the global best calculation. The standard PSO updates the swarm's positions in the exploitation step as

$$P_i^{K+1} = P_i^k + v_i^{K+1} \tag{19}$$

Where

$$v_i(t+1) = w \times v_i(t) + c_1 \times rand \times (lbest - P_i(t)) + c_2 \times rand \times (gbest - P_i(t)) \tag{20}$$

v represents the velocity of swarms. In the proposed solution the V_d are updated by adding the global nature of GSA in equation 6 as

$$v_i(t+1) = w \times v_i(t) + c_1 \times rand \times acc_i + c_2 \times rand \times (gbest - P_i(t)) \tag{21}$$

Where acc_i is the acceleration in GSA for V_i. This acceleration is computed as

$$acc_i(t) = {F_i(t)}/{M_i(t)} \tag{22}$$

Where force, $$F_{ij}(t) = G(t)\frac{M_{pi}(t)\times M_{aj}(t)}{R_{ij}(t)+\varepsilon}(x_j(t) - x_i(t)) \tag{23}$$

Normalized mass, $$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \tag{24}$$

Mass, $$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{25}$$

The gravitational constant computed as

$$G(t) = G_0 \times e^{(-\beta\frac{t}{t_{max}})} \tag{26}$$

$fit_i(t)$ is the fitness value calculated using equation 3 for each set of swarm's position. This is the exploration phase output which is fed into the exploitation phase. The minimum of this from a set of positions is the best value so far, and the maximum of this is the worst value. This way, GSA's exploitation step is inherited into PSO to make it converge at a global solution.

The constant gravitational G in GSA is perturbed by logistic mapping to add the chaotic ergodicity and pseudo randomness in the exploitation phase. The, G_0 and β are constants that are specified for a particular problem. The $G(t)$ in our proposal is calculated as:

$$G(t) = x_n \times (w_{max} - t \times (w_{max} - w_{min})/t_{max}) \tag{27}$$

Where x_n is the chaotic variable. It is made adaptive by multiplying with adaptive weights, which changes in each iteration$t$.w_{max} and w_{min} are weights bounds. The system parameter r in the logistic map is considered 4 for the best chaotic behavior from table 1. The pseudo-code for the proposed hybrid optimization is shown in algorithm 2.

Algorithm2**:** Pseudo-code for hybrid optimization PSOCGSA

Input: searching space dimension D, WSN area limit, $\boldsymbol{n \Rightarrow number\ of\ swarms}$, $\boldsymbol{t_{max} \Rightarrow maximum\ iterations}$

Output:$\boldsymbol{bestPosition}$ ⇒optimal $\boldsymbol{V_d}$'s best positions

1. Generate the initial swarms' positions $\boldsymbol{P_i^{j=1,2}}$ with logistic mapping
2. Initialize $\boldsymbol{gbestscore} = \infty$
3. For $\boldsymbol{t = 1{:}\,t_{max}}$
4. Check for WSN area constraints
5. Calculate the fitness value $\boldsymbol{fit_i(t)}$
6. If $\boldsymbol{fit_i(t) < gbestscore}$
7. $\boldsymbol{gbest_i = P^{j=1,2}_{fit_{index}(t)}}$
8. Endif
9. $\boldsymbol{worst_i = \max(fit_i(t))}$
10. $\boldsymbol{best_i = \min(fit_i(t))}$
11. Calculate mass $\boldsymbol{M_i(t)}$
12. Apply chaotic logistic mapping for constant gravitational $\boldsymbol{G(t)}$
13. Calculate force $\boldsymbol{F_{ij}(t)}$ and acceleration $\boldsymbol{acc_i(t)}$
14. Update the swarm's velocity by $\boldsymbol{acc_i(t)}$, $\boldsymbol{gbest_i}$ by equation 6 and add this to the current position $\boldsymbol{P_i^k}$
15. $\boldsymbol{bestPosition = gbest_i}$
16. End for loop

4. Experimental Setup

We proposed a Hybrid multi-objective chaotic particle swarm optimization with gravitational search algorithm (MOCPSOGSA) to select the location of sensor nodes for minimum consumption energy, maximum sensitivity area and maximum network lifetime in SHM of Guangzhou New TV Tower, China. We consider the data of the real mode shape of GNTV tower China. The GNTV tower is completed in 2009 and becomes the tallest tower with 610-meter height with a 156-meter antenna. We set up the GNTV tower's environment in MATLAB software and placed the sensors node placement on the building structure area by the MOCPSOGSA algorithm. The performance of the proposed MOCPSOGSA sensor node placement is carried out in the MATLAB software and compare with the existing approaches of sensor node placement in SHM. The input and design parameters of the proposed algorithm are mentioned in table 2.

Table 2: Parameters and values use in simulation

Parameters	Values
Deployment area	50*450
Number of nodes	40
Initial node of energy	2J
Transmission range	60
Number of search agents	20
Maximum iteration	100
Chaos constant	a=0.5 and b=0.2
PSO coefficient constant	C1=0.2, C2=2;
Alfa	20
Gravitational constant	100

The performance of the proposed multi-objective CPSOGSA optimized WSN based SHM algorithm are evaluated in terms of residual energy, cover area and network lifetime. Fig. 3 shows the convergence curve comparison among the CPSOGSA algorithm and PSO algorithm for the optimal sensor node placement. The PSO algorithm shows premature convergence that means the optimal global value of the best function is not achieved. The hybrid multi-objective CPSOGSA algorithm shows early and fast convergence with the optimal global solution of the objective function.

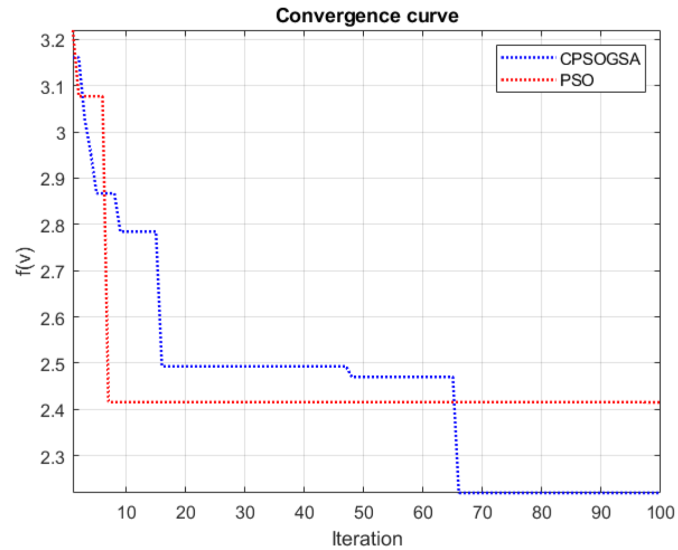


Fig. 3: Convergence curve comparison among CPSOGSA and PSO

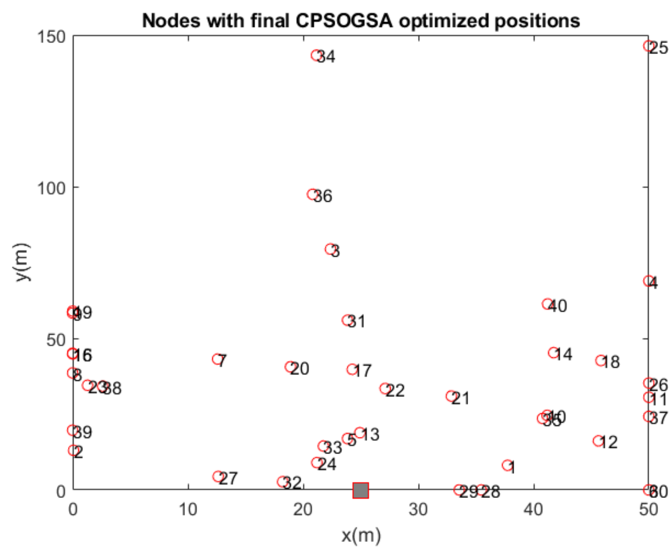


Fig. 4: Sensor nodes with optimal position of CPSOGSA

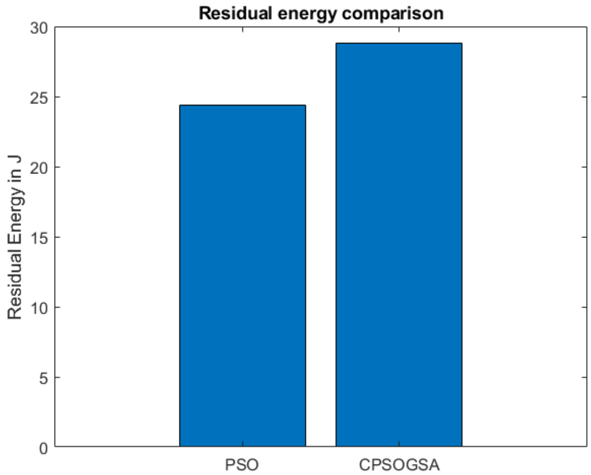


Fig. 5: Residual energy comparison

Fig. 4 shows the optical sensor node placement after the multi-objective CPSOGSA optimization. The sensor node placement is done based on the optimal distance among the nodes and their communication. Fig. 5 compares the average residual energy of PSO and CPSOGSA optimized sensor node placement by varying the sensor nodes' position with optimal residual energy. The residual energy is the remaining energy of the node after completing the communication task. The stable residual energy is necessary for the nodes to select the optimal routing path. In the SHM task, the sensor node residual energy is higher in the multi-objective CPSOGSA algorithm than the PSO optimize algorithm. The higher residual energy of sensor nodes means the greater the stable network's probability and optimal routing. The average residual energy of the CPSOGSA optimized network is greater than the PSO optimized sensor node, as shown in fig. 5. The monitoring task is performed efficiently due to the less consumption energy of the nodes. The sensor nodes less consumed energy is minimized the cost of the WSN based SHM system.

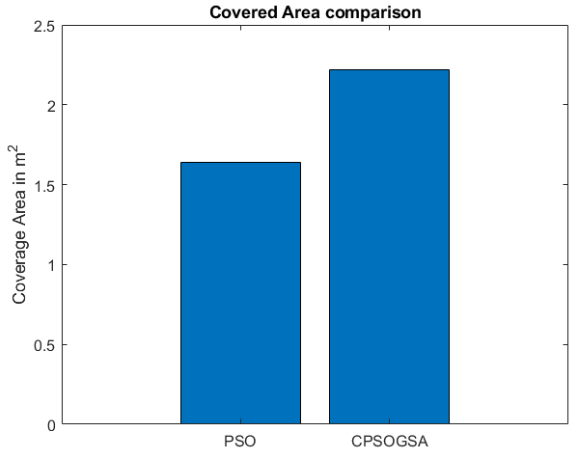


Fig. 6: Cover area comparison of WSN based SHM

The sensitivity factor of the sensor node is related to the covered area of the network. The sensitivity term should be maximum for the large area coverage in the sensor node network. Fig. 6 shows the comparison among the cover area in the PSO and CPSOGSA optimized algorithm based on the sensitivity analysis. The maximum coverage area is achieved in the case of the multi-objective CPSOGSA algorithm than the PSO algorithm.

The outcomes of the two terms, residual energy and the coverage area, are directly proportional to the network's lifetime. Fig. 7 shows the comparison among the network lifetime for PSO and CPSOGSA optimized of SHM task. The network lifetime of the multi objective-based CPSOGSA algorithm is greater than the PSO optimized network.

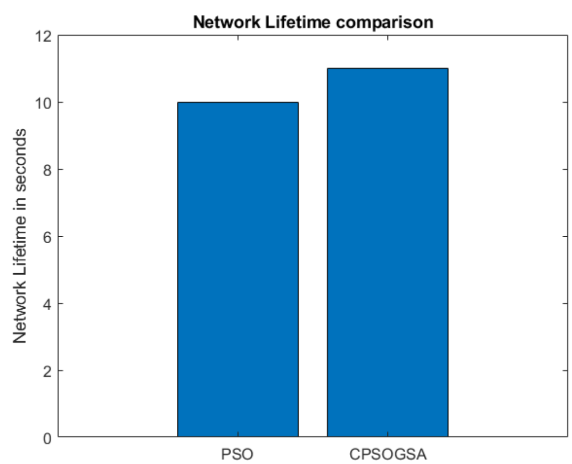


Fig. 7: Network lifetime of WSN based SHM system

5. Conclusion

A structural health monitoring task is presented based on the multi-objective CPSOGSA algorithm for the GNTV tower china. A novel hybrid algorithm is developed by combining chaotic PSO with GSA and tested with the Pareto solution environment. The Pareto environment is achieved the best solution of the objective function in terms of residual energy, sensitivity area, and network lifetime. efficient communication and optimal distance is achieved simultaneously in the multi-objective CPSOGSA algorithm. The suggested algorithm shows optimal results in each case like network lifetime, cover area and residual energy. The maximum value of residual energy is enhanced the network lifetime. The optimal structural health monitoring task is performed with the multi-objective CPSOGSA algorithm optimized WSN network algorithm.

In future, the proposed method can be tested on the historical dataset. The multi-objective algorithms will be used in other applications like network management, reconfiguration and recognition field.

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