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OPTIMUM REDUNDANCY ALLOCATION OF WTP AND COMPARATIVE ANALYSIS USING SMO & PSO TECHNIQUES

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Abstract

Constraint optimization Redundancy Allocation Problem (CoRAP) is a complex real world integer programming problem. Many researchers have used various techniques to solve CoRAP. Many complex problems are being solved by various evolutionary techniques, and among these Spider Monkey Optimization algorithms (SMOs) and Particle Swarm Optimization algorithms (PSOs), which focus on the behavior of monkeys and collective nature of birds in a swarm, are the most promising and recent interests of researchers. Therefore, in this article, SMO and PSO is tuned to solve the problem based on integer programming, CoRAP for Water Treatment Reverse Osmosis (RO) Plant (WTP) subject to cost constraint. The results obtained using SMO are compared with the results obtained by applying the same problem to the PSO algorithm. SMO and PSO are implemented using MATLAB. The findings demonstrate the better performance of SMO.

Keywords: *reliability, Redundancy Allocation Problem (RAP), Spider Monkey Optimization (SMO), Particle Swarm Optimization (PSO).*

INTRODUCTION

Nowadays, the company's success in competitive market is highly dependent on the ability to efficiently allocate high output and quality to the needs of the client. As a significant sub-field of reliability engineering, the importance of optimizing reliability has been revoked over the last few years. System reliability is one of the most important issues in building a variety of software and computer hardware. Maintaining a balance between reliability and other available resources is a major challenge in the process of building a highly efficient system. Redundancy allocation is one of the methods used to improve the reliability of the system. There have been various kinds of components for each subsystem in RAP, with various levels of parameters such as cost, reliability and weight. Redundant components may be of the same type within a subsystem or multiple kinds where in case of component mixing is permitted. Zaretalab et al. (2020) proposed a model for solving multi-state RAP by using parameter-tuned Memetic Algorithm (MA) and then compared the obtained results with Genetic Algorithm (GA).

There are various Reliability Redundancy Allocation Problems RRAPs considered in the literature, such as parallel, series (Chern, 1992), series-parallel (Billionnet, 2008;, Yalaoui, Chu, Chatelet, 2005; Jiansheng et al., 2011) and k-out-of-n (Li et al., 2016). Agrawal

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et al. (2021) evaluate the profit function of a Water Treatment Reverse Osmosis (RO) Plant using the Regenerative Point Graphical Technique (RPGT). Kumar, Garg, and Goel (2019) examined the behavioral analysis of a washing unit in paper industry for system parameters using RPGT. To successfully solve RRAPs, a new swarm intelligence approach known as a Particle-based Simplified Swarm Optimization (PSSO) algorithm was introduced by Huang (2015).

Many researchers considered the component mixing option to be active with the redundancy strategy taken. For work on hot standby and cold standby systems, one can refer to the work done by (Boland et al. 1992; Singh & Misra, 1991;, Romera, Valdés, & Zequeira, 2001). Ardakan and Rezvan (2018) investigate a cold standby RRAP and evaluated the efficiency of the standby strategy. Many researchers have used various techniques to solve Constraint optimization Redundancy Allocation Problem (CoRAP). Many complex problems are solved by various evolutionary techniques, and among these Spider Monkey Optimization algorithms (SMOs) and Particle Swarm Optimization algorithms (PSOs), which focus on the behavior of monkeys and collective nature of birds in a swarm, are the most promising and recent developments of researchers. SMO and PSO has a wide variety of applications in biological, medical and electrical engineering.

Water treatment is important in the world because access to clean water is limited in the world and demand is high. It is vital to protect humans from harmful chemicals, metals, and other pollutants that are harmful to human health and the planet's ecosystem. The emergence and implementation of water treatment technology is driven primarily by three main factors: the discovery of uncommon pollution, the announcement of new water quality standards, and the cost. Reliability optimization makes it possible for efficient use of resources and leads to increased productivity and reduced waste of money, property and labor.

The research mainly aims to solve CoRAP for WTP by using two techniques named as SMO and PSO method and then compared their results.

LITERATURE REVIEW

Optimization Techniques

Spider Monkey Optimization (SMO)

SMO is an algorithm based on the population, stimulated by the spider monkeys' social activities. It is based on the intelligent behavior of spider monkeys' which imitates the social structure of fission–fusion. As real-world problems are becoming complicated the need for instant, practical and straightforward optimization algorithms is expanding among researchers in different fields. SMO is a modern, nature-inspired meta-heuristic algorithm and is a hit-and-test iterative technique suitable for global optimization over discrete and continuous spaces. It has performed superior to other swarm-based algorithms based on intelligence, which is evident from the fact that it provided better performance when evaluated on different benchmark problems. Since some controlled variables are included in SMO due to which implementation of SMO in various types of optimization problems becomes simpler. Spider monkey is a South American monkey species that lives in a large group and exhibits awareness in social interaction and food hunting (Carpenter, 1935).Spider monkeys in a group (under leader of a group) and subgroups (under leaders of subgroup) search for food. In particular, the group is headed by a senior female who is in control of discovering food sources. Starting with a single group, they forage for food and are divided into subgroups to spread the search in different directions to better explore the region. Fission–fusion social structure of spider monkeys is depicted in Figure 1.

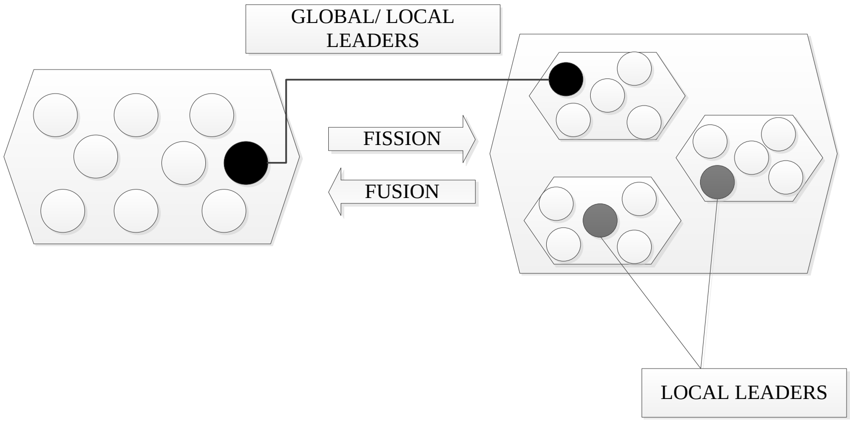

Figure 1. Spider Monkeys' Fission-Fusion Social System

Most frequently, subgroups are headed by a woman who takes the decision and designs a well-organized foraging path each day. Team members meet among themselves and other long-distance group members using a specific call. Also every spider monkey has unique sound which other individuals within the group can easily identify to find out who is calling. A subgroup leader can split the group again if it fails to find a food source for (McFarland-Symington, 1990). Once the number of groups approaches its highest level, all the subgroups are incorporated into one large main group by the leader of the main group and then again split them into many subgroups. The fission and fusion process repeats until the spider monkey swarm ends up with a good food source. For numeral optimization, the search mechanism is employed in SMO. Table 1 indicates the terms used in the SMO and Figure 2 displays the flow chart for the Spider Monkey Optimization Algorithm's.

Table 1. *Terminology used in SMO*

Terminology	Description
LL	Local Leader
GL	Global Leader
Div	Division
L	Local
G	Global
I	Iteration Counter
Pc(i)	Position Counter
FT	Fitness function

Literature Review of SMO

Bansal et al. (2011) introduce SMO by studying the spider monkeys foraging activity. A self-adaptive algorithm for SMO was introduced by Kumar, Sharma, and Kumari (2011). For the community of electromagnetic, Al-Azza, Al-Jodah, and Harackiewicz (2016) applied SMO as an optimization technique. A survey on SMO, its applications and variants was conducted by Agrawal, Rastogi, and and relative performance with other algorithms were presented. Recently, Akhand et al. (2020) used a modern Discrete Spider Monkey Optimization (DSMO) approach to solve the problem of travelling salesmen. Gupta, Deep, and Bansal (2017) made an effort to solve confined continuous optimization problems employing SMO algorithm for restricted optimization issues. The authors recommended an updated SMO in this paper using Deb's constraint strategic approach to overcome optimization issues. The updated version was called algorithm for Constrained SMO (CSMO). Sharma et al. (2017) proposed new search feature in SMO called Power Law-based Local Search (PLLS). Cheruku et al. (2017) used the SMO rule using novel exercise method for diabetes classification and suggested that SMO could be used to describe an efficient rule miner for diabetes diagnosis called SM-Rule-Miner. Relative to other metaheuristic – based rule mining algorithms, it was found that SM-Rule-Miner obtained the most significant accuracy sensitivity rating and the second best average classification performance rating. Sharma et al. (2017) addressed that capacitors of specific sizes would have been positioned in the distribution system to minimize the failures in delivery and transmission. Sharma et al. (2016) addressed a paper in which SMO has been used to determine the optimal PIDA controller parameters to control the induction motor. This was the first attempt to achieve such a target using SMO. The outcomes were correlated with the Dorf approach and PSO, and it was noticed that better results were provided by SMO than that of the two methods. Nayak et al. (2016) addressed a mathematical representation of a multi-machine power system based on a VSC-HVDC link. In order to minimize power oscillations and increase the dynamic stability of the machining power systems based on VSC-HVDC, the PI controller selected by the SMO technique is operated.

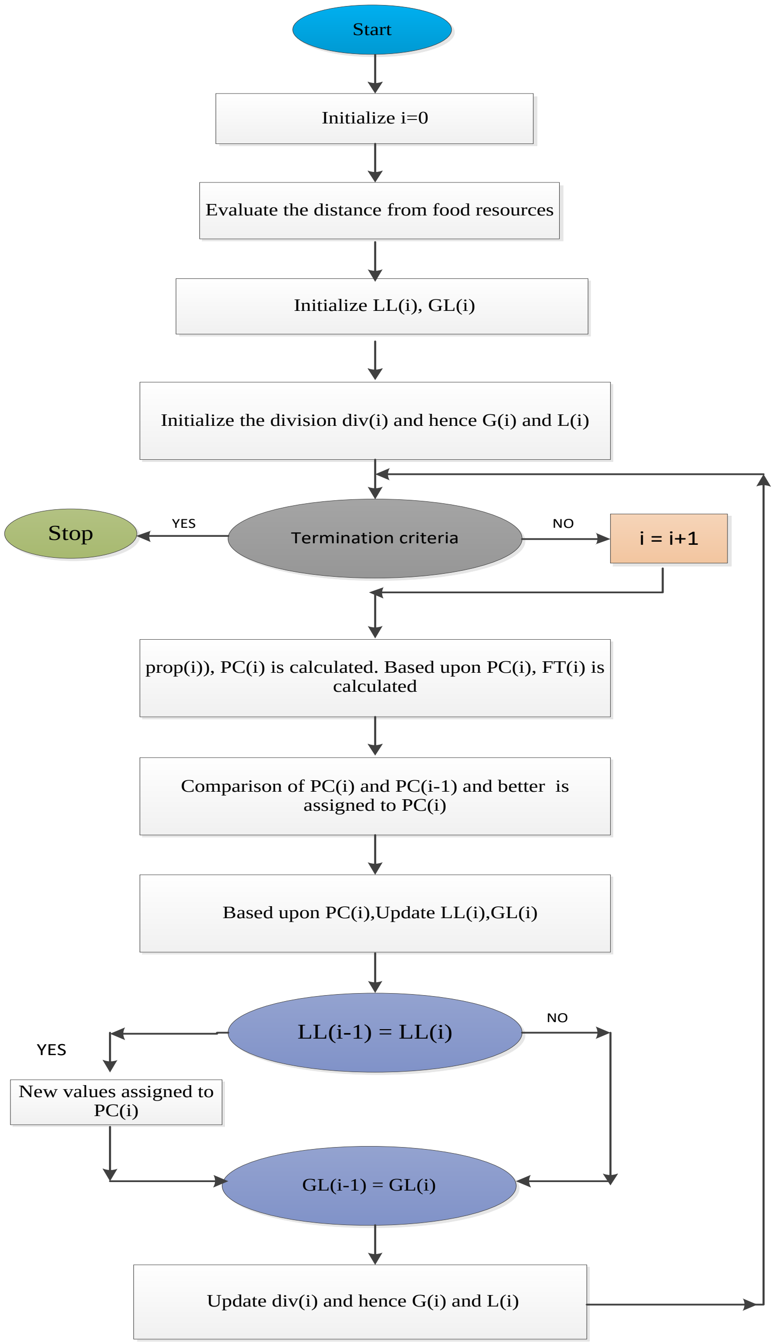

Figure 2. Flowchart for SMO

Many researchers have done the comparative analysis of SMO with various optimization techniques. A comparative analysis of Hybrid Particle Swarm Optimization with three algorithms was proposed by Arora, Sood, and Keshari (2016) over different benchmark concerns and t-test was applied to evaluate their statistical significance. Results suggested that algorithm efficiency was unique for different functions. Deb, Chakraborty, and Deb (2019) apply Genetic Algorithm (GA) and Spider Monkey Optimization (SMO) techniques to locate the optimal location and dimensions of DG for voltage security state improvement of a reconfigured distribution system. Darapureddy, Karataou, and Battula (2021) develop a new Content-Based Image Retrieval System based on Optimal Weighted Hybrid Pattern using a modified algorithm named as Improved Local Leader-based Spider Monkey Optimization (ILL-SMO) algorithm which optimized the weight, intended to maximize the precision and recall of the retrieved images. Khare et al. (2020) prioritize a hybrid classifier model named as Spider Monkey Optimization and Deep Neural Network (SMO-DNN) for detecting intrusion. It reduces the size and then binary separation is done using DNN. Nandgave-Usturge et al. (2020) developed a new algorithm namely Water Spider Monkey Optimization (WSMO) which evaluated the highly trust factor nodes. Then in the next step, secure nodes are identified and routed the best path. Xia et al. (2021) developed a hybrid algorithm which incorporates both Discrete Spider Monkey Optimization (DSMO) and Genetic Algorithm (GA) called as DSMO-GA for resolving the issue of Vehicle Routing Problem with Stochastic Demands (VRPSD). Patel et al. (2021) articulated a Local Neighbor Spider Monkey Optimization algorithm (LNSMO) for solving problems of data clustering. More research revealed that SMO was consistent and computationally cheap as compared to other algorithms.

Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO), a meta-heuristic algorithm focused on shoals and flocks social behavior, was proposed by Kennedy and Eberhart (1995). PSO is a widely used stochastic meta-heuristic population-based optimization algorithm that has so far been effective on a variety of non-continuous and non-linear optimization algorithms. PSO technique is inspired by the collective nature of birds in a swarm. In PSO, population is termed as swarm and the individuals are termed as particle. Each particle's position and velocity are the two most important factors. In the swarm, each particle moves with their own position or velocity in the search space and trying to find the optimum position or velocity. A swarm of particles flies through the solution space in a PSO algorithm to find the best locations. Every particle's location is a possible solution to the optimization problem. The particle's velocity is used to move it around in search of the best location. Each particle updates its velocity and location based on its own and the swarm's previous experiences. This algorithm can solve even the most difficult mathematical problems. As a result, PSO has become a fascinating tool for researchers and has been used in a variety of areas. The flow chart for the PSO algorithm is depicted in Figure 3.

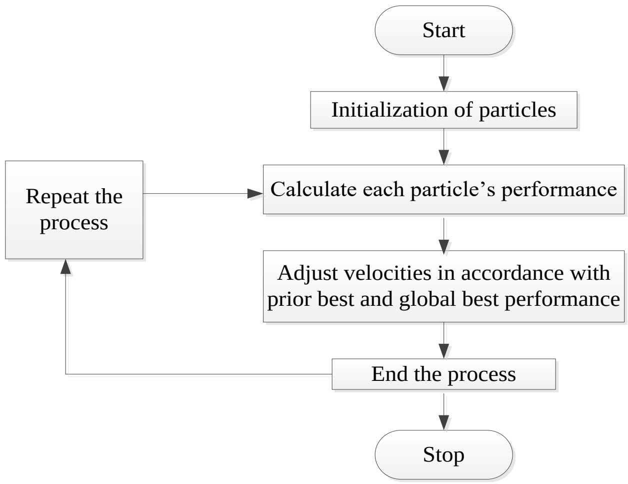

Figure 3. Flowchart for Particle Swarm Optimization (PSO)

Literature Review of PSO

Shi and Eberhart (1999) examine the performance of PSO by applying on four benchmark functions. The experimental results showed that the performance of PSO can be improved by using an adaptive inertia weight. Further Eberhart and Shi (2000) compared the performance of PSO using inertia weight and constriction factors on five benchmark functions which results that the use of constriction factor is better than inertia weight. Coelho and Mariani (2006) apply the hybridization of PSO with Quasi-Newton local search method for solving economic dispatch problem. Meneses, Machado, and Schirru (2009) apply PSO technique to optimize a combinatorial problem such as the Nuclear Reactor Reload Problem. Zhu et al. (2011) use PSO algorithm to solve multi-objective portfolio optimization problem by testing restricted and unrestricted risky investment portfolios and achieving optimal risky portfolios.

Sarkar, Roy, and Purkayastha (2013) apply hybrid PSO algorithms for data clustering which gave optimal number of clusters and results in better forecasting and analysis of data. PSO has been applied to numerous problems in several areas of sciences. For example, Payan and Azimifar (2016) apply PSO algorithm to increase the heat transfer and obtained the optimal shape of cavity. In healthcare, Srisukkham et al. (2017) used PSO algorithm in diagnosing the disease of leukaemia using microscopic images. Zhao et al. (2018) adopt PSO algorithm to obtain the global optimization of the diesel engine–Organic Ranking Cycle (ORC) combined system. Nogueira et al. (2018) used PSO algorithm for the optimal design of a hybrid diesel-ORC/photovoltaic system. Leite et al. (2018) applied PSO algorithm to optimise geometry for the spring and the dimple by minimizing the stresses in the nuclear fuel bundle Spacer Grid (SG). Ajdad et al. (2019) used PSO algorithm to optimize solar linear Fresnel reflectors geometry. Devi and Garg (2017) applied Hybrid Genetic Algorithm combined with PSO named as (HGAPSO) to solve Redundancy Allocation Problem (RAP).

MATERIALS AND METHODS

System Description

Water treatment RO plant comprises of the following components which include Raw Water Forwarding Pump (RWFP), Flow Indicators (FI), Pressure Indicators (PI), Multi Media Filter (MMF), Cartridge Filter (CF), Antiscalant Dosing pump with Tank (ASD), High Pressure Pump (HPP), RO System, Product Water Storage Tank (PWST), and Reject Water Storage Tank (RWST). The process diagram of Water Treatment RO Plant is shown in Figure 4 and Table 2 describes the terms used in the Water Treatment Plant.

Table 2. *Terminology used in Water Treatment Plant*

RWT	Raw water tank, client scope
	Battery limits
LSH	Level Switch High
LSL	Level Switch Low
⋈	Valves
CIP	Clean in place
LPS	Low pressure switch
HPS	High pressure switch

1. RWFP
   This pump is used to feed water to the system at the desired pressure and flow.
2. FI
   It is a device installed into a pipe to provide a visual of actual flow rate.
3. PI
   Pressure indicators are used to verify the pressure at the inlet and outlet of each unit.
4. MMF
   It is used for removing macro particles from the feed water. It consists of Anthracite and Graded Quartz.
5. CF
   This is a five-micron filter that removes micro particles from the feed water to increase membrane life by minimizing membrane fouling.
6. ASD
   This is an automated metering pump used for dosing chemicals prior to the RO method to eliminate scaling on the surface of RO membranes, thus increasing the life of the membranes.
7. HPP
   This pump produces a pressure above the osmotic pressure allowing reverse osmosis to occur.
8. RO System
   It consists of RO Pressure Vessels and RO Membranes
   (i) RO Pressure Vessels
   They are vessels that can absorb the high-pressure load produced by the high-pressure pump and are often used to house the RO membranes.
   (ii) RO Membranes
   This is the center of the methods and the purification of the water is achieved through reverse osmosis. The feed water is separated into two sources: the low TDS water stream called the permeate stream, and the other is the high TDS water stream called the Reject stream.
9. PWST
   This is used to store permeate water for use in the process or drinking.
10. RWST
    It is used to hold the high TDS water and used to wash the board etc.

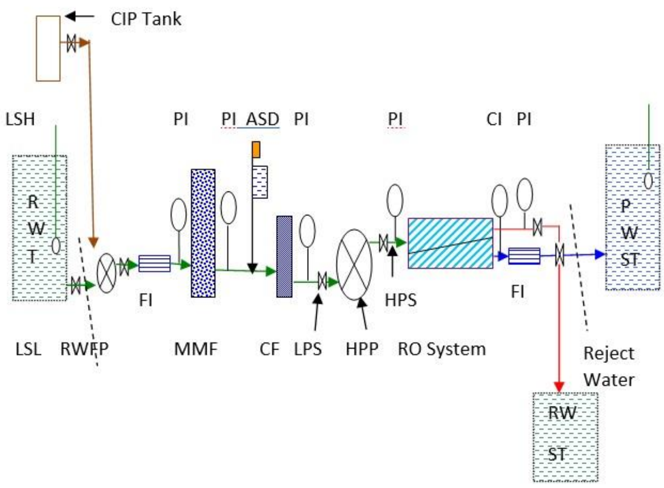

Figure 4. Process Diagram of Water Treatment Plant

Problem Formulation

Problem is to solve CoRAP for Water Treatment Plant. The terminology used in developing and solving the problem is mentioned in Table 3. Further optimization problem and cost constraints are mentioned as equation (1) and equation (2) respectively. To maximize the system reliability is used as objective function for SMO and PSO. Table 4 represents the failure rate and the costs associated with each subsystem.

Maximum Cost restriction MC = 5550000

Problem to maximize*:*

$$RS = \prod_{i=1}^{10}[1-\{FR_i(M_i)\}^{n_i}] \quad (1)$$

Subject to cost constraint:

$$\sum_{i=1}^{10} C_i(M_i)n_i \leq 5550000 \quad (2)$$

Table 3. *Terminology used in Problem formulation*

M_i	i^{th} **component**
n_i	No. of redundant units connected with $M_{i^{th}}$ unit
$R_i(M_i)$	Reliability of $M_{i^{th}}$ unit
$FR_i(M_i)$	Failure Rate of component $M_{i^{th}}$ unit
RS	Overall system reliability
$C_i(M_i)$	Cost of M_i subsystem
$n=10$	Total units
MC	Maximum cost

Table 4. *Failure rate and Cost of each subsystem*

Subsystem	Failure rate $FR_i(M_i)$	Cost of each Subsystem $C_i(M_i)$
M_1	0.01	19500
M_2	0.0861	45000
M_3	0.0247	120000
M_4	0.0344	290000
M_5	0.1813	140000
M_6	0.1393	175000
M_7	0.0952	95000
M_8	0.0198	125000
M_9	0.0247	500000
M_{10}	0.0952	200000

RESULTS AND DISCUSSIONS

In this section, CoRAP results are discussed through tables and graphs. The decision variables are $n_i, i = 1,2,\dots,10$.The original reliability value for water treatment plant is 0.4695. Reliability obtained using SMO can be seen in Table 5 and Table 7 shows reliability obtained using PSO for a given plant. Table 6 displays the results obtained for RAP using SMO and PSO for n variables in terms of increase in reliability, respectively. From Table 5, it is clear that the maximum reliability obtained using SMO is 0.998. It can be seen in Table 6 that the reliability obtained using SMO is higher than the reliability obtained by PSO. Figures 5(a) and 5(b) displays the reliability obtained for the decision variables and number of units for various subsystems to obtain desired reliability. It is observed from the figures that the reliability shows increasing decreasing trend for the decision variables but the maximum reliability obtained for the variables is not more than 0.998.

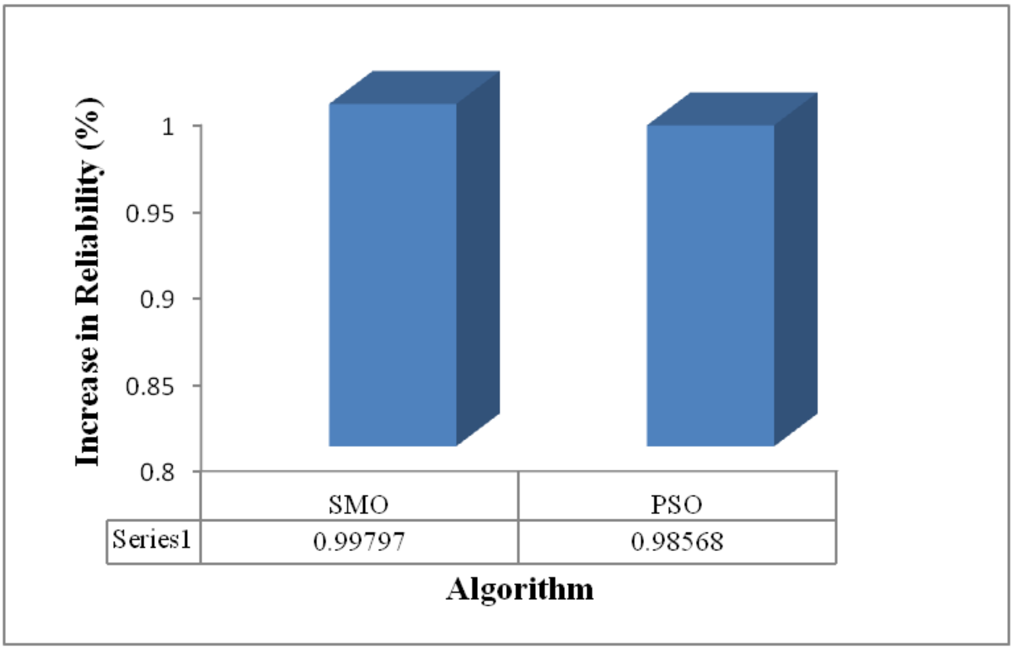

Figure 5(a). Increase in Reliability

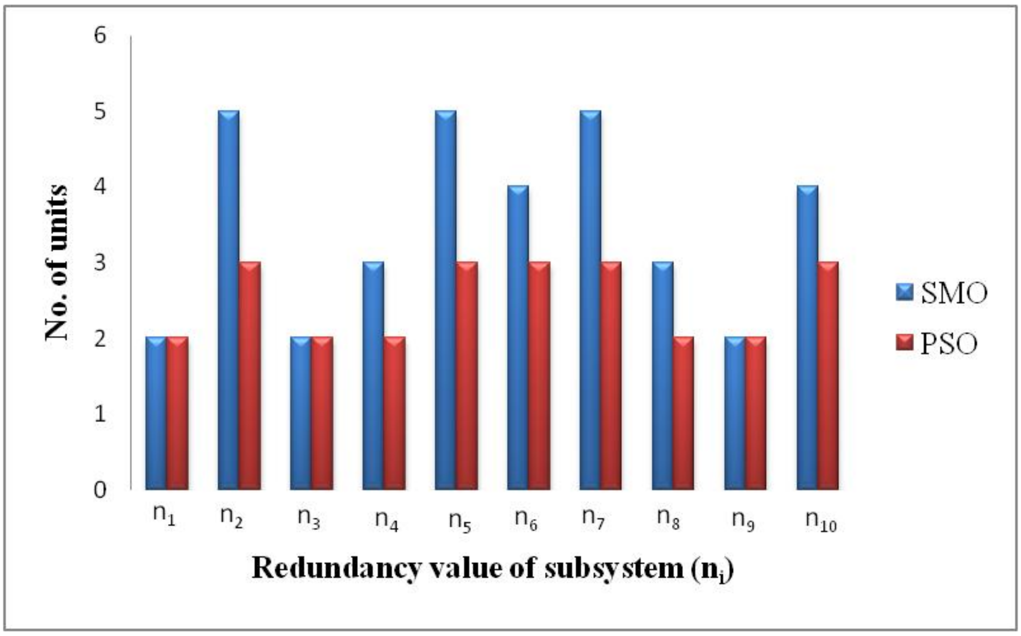

Figure 5(b). Number of units for various subsystems to obtain desired reliability

Table 5. *Reliability obtained for subsystems using SMO*

RS	n_1	n_2	n_3	n_4	n_5	n_6	n_7	n_8	n_9	n_{10}
0.99797	2	5	2	3	5	4	5	3	2	4
0.982477	6	3	6	3	3	5	2	2	2	3
0.955593	4	3	6	3	4	5	2	2	1	2
0.894395	6	6	6	4	4	4	1	2	2	2
0.856378	4	4	6	5	2	5	1	1	2	3
0.782709	5	4	6	1	1	4	2	2	3	5
0.725503	5	3	6	1	4	1	2	5	1	1
0.679986	5	1	6	1	4	1	2	2	3	1
0.612036	5	1	6	3	1	4	1	2	4	1
0.000090	5	3	6	5	4	6	3	2	6	3

Table 6. *Comparative analysis of results obtained using SMO and PSO*

Algorithm	**Result of RAP**											**Increase in reliability (%)**
	n_1	n_2	n_3	n_4	n_5	n_6	n_7	n_8	n_9	n_{10}	**RS**	
SMO	2	5	2	3	5	4	5	3	2	4	0.99797	52.847
PSO	2	3	2	2	3	3	3	2	2	3	0.98568	51.618

Table 7. *Reliability obtained for given plant using PSO*

RS	n_1	n_2	n_3	n_4	n_5	n_6	n_7	n_8	n_9	n_{10}
0.985679	2	3	2	2	3	3	3	2	2	3
0.978972	2	2	2	2	3	3	3	2	2	3
0.970937	2	2	2	2	3	3	3	2	2	2
0.962968	2	2	2	2	3	3	2	2	2	2
0.953434	1	2	2	2	3	3	2	2	2	2
0.937467	1	2	2	2	3	2	2	2	2	2
0.919273	1	2	2	2	3	2	2	1	2	2
0.897195	1	2	2	2	3	2	2	1	1	2
0.875647	1	2	1	2	3	2	2	1	1	2
0.851950	1	2	1	2	2	2	2	1	1	2

CONCLUSIONS

As real-world optimization problems such as CoRAP become complex and complicated day by day, there is a growing need for rapid, simple and efficient optimization algorithms among researchers in a variety of fields. SMO is a modern meta-heuristic algorithm inspired by a nature iterative technique for global optimization over continuous and discrete space. The research provides a summary of the work carried out using the SMO and PSO technique. The Percentage increase in reliability obtained by SMO and PSO is 52.847, 51.618 respectively. However, the rise in the value of reliability via SMO is more than PSO. Hence Performance of SMO is better than other algorithms used in this research. These findings can also allow the manufacturer to achieve the highest possible reliability. Moreover, if redundancy is allocated at subsystem level as per results, then failure rate of subsystem can be reduced drastically, it will also lead to increase in safety, profitability, etc.

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