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# IDENTIFICATION OF OPTIMAL POLYMERIC BLEND (SiR-EPDM) USING SOFT COMPUTING OPTIMIZATION TECHNIQUES-PSO AND GA

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## ABSTRACT

This paper presents the application of the soft computing optimization techniques such as Particle swarm Optimization (PSO) and Genetic algorithm (GA) in order to identify the Optimal Blend of Silicone Rubber (SiR) and Ethylene Propylene Diene Monomer (EPDM). The behavior of the polymeric materials such as SiR and EPDM are found to be un-satisfactory, due to their inherent shortcomings as the homo polymer. To overcome those limitations and also to fully avail the superior properties of both the materials, blending of SiR-EPDM is done. As per ASTM and IEC standards the blends are tested, in order to find their mechanical properties like tensile strength (TS) and elongation at break (EB) and also the electrical properties like volume resistivity (VRY) and surface resistivity (SRY), arc resistance (AR) and comparative tracking index (CT). It is really hard to choose a optimal blend (OB), among the large number of electro-mechanical parameters. In order to identify the OB with superior performance indices compared to that of the constituent polymers, optimization techniques are used. The determination of the optimal blend of SiR-EPDM is formulated as a multi-objective optimization problem with the objective of maximizing the electrical and mechanical properties. Based on the weightage assigned for various electrical and mechanical parameters, the Optimal Blend Problem (OBP) can provide a improved performance as desired. Particle swarm optimization (PSO), part of the swarm intelligence family, is known to effectively solve large-scale nonlinear optimization problems. In this paper, the PSO is used to find the optimal blend ratio (OBR) for cable applications. To high-light the superiority of PSO and also to validate the results, a comparison has been made with Genetic Algorithm (GA) Technique.

**Keywords:** Silicone Rubber , Optimal Polymeric Blend, Ethylene Propylene Diene Monomer, Particle Swarm Optimization, Genetic Algorithm, Equal Weights (EW), Un-equal Weights (UEW).

## INTRODUCTION

Among the several conventionally available polymers, Ethylene Propylene Diene monomer (EPDM) and Silicone Rubber (SiR) are the commonly used elastomer materials for high voltage applications. EPDM, due to its stable saturated polymer backbone structure, has excellent resistance to heat, oxidation, ozone and weather ageing. It responds well to high filler and plasticizer loading, providing economical compounds. They develop high tensile and tear properties, excellent abrasion resistance as well as improved oil swell resistance and flame retardance [1, 2, 3]. But the EPDM has inferior electrical properties compared to SiR. Silicone rubber is non-reactive, stable and resistant to extreme environments with temperatures ranging from -55°C to +300°C along with maintenance of its useful properties. Silicone is widely used in harsh environments mainly for its hydrophobic property. However Silicone rubber, as a material is very costly and has poor mechanical properties. [4, 5] Restricted properties and limited use of homo polymers has given rise to exploration of composites, Co-polymers, blends, etc., Blending is an attractive way of producing a new material as it does not involve cost and technical un-certainties as that in synthesizing a new polymer. It has the potential to combine the attractive properties of both the constituents in the blend. It is believed that with proper formulation, the blends can provide low cost alternatives to existing materials with superior performance [6, 7]. Blending of SiR with EPDM is a useful approach for the preparation of a new rubber material with better ageing resistance. This blend may provide a kind of rubber-rubber mixture which may become technologically important as they combine the characteristics of both. The effect of SiR/EPDM blend ratio on the electrical and mechanical properties are investigated [8, 9, and 10].

The performance of SiR-EPDM blend is characterized by the 4 electrical and 2 mechanical parameters. It must be mentioned here that the identification of a optimal polymer blend is totally application specific as some may require excellent mechanical properties such as good tensile strength or tear resistance while some may require excellent electrical properties. So in a practical situation, it is very difficult to identify the OBR for a particular application. Generally, the required mechanical parameter has to be matched against certain relevant electrical parameter in order to identify the optimal blend. For the present investigation, 5 different blends have been prepared as given in appendix-I. This approach is used by Rajaprabu [7] and SiR/EPDM blend composition of 50/50 was chosen as optimal blend. For the 5 experimentally prepared blends, electrical parameters such as volume and surface resistivity, arc resistance and comparative tracking index as well as the mechanical parameters like tensile strength and elongation at break are measured using the suitable experimental procedures (refer appendix II). The various electrical and mechanical parameters are plotted against the blend ratios. Out of different blend ratios, the one with 50:50 blends

VOL. 7, NO. 9, SEPTEMBER 2012 ISSN 1819-6608
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possessed the high performance parameters in view of both the electrical and mechanical properties [7, 8, 9].

From the literature, it is evident that computational techniques like genetic algorithm and artificial neural network have been applied to solve a variety of complex engineering problems. [11, 12, 13] Herein the authors have made an attempt to use particle swarm optimization approach to identify OBR for a certain specific application. The focus of this work is to identify optimal blend of SiR/EPDM with the objective of maximizing the certain desired electrical and mechanical parameters. The aim of this paper is to investigate the suitability of optimization algorithms such as PSO for the specified OBP with the objective of maximizing the performance indices.

Particle swarm optimization is a population based search algorithm characterized as conceptually simple, easy to implement and computationally efficient, similar to the other population-based evolutionary algorithms. PSO is initialized with a population of random solutions Unlike the most of the evolutionary algorithms, each potential solution in PSO is also associated with a randomized velocity and the potential solutions called particles, are then ‘‘flown’’ through the problem space. The performance of PSO algorithm is compared with GA based optimization. The results show that PSO based approach performs better in terms of solution quality, accuracy and convergence time [14, 15, 16, 17, 18]. In PSO, any weight age (EW/UEW) can be randomly assigned to any particular (electrical/mechanical/both) parameter.

In the author’s previous work, PSO is implemented with EW of 0.5 each and UEW (SRY=0.4 and EB=0.6) for set 2(SRY-EB), provided with zero weight age for remaining 4 parameters (VRY, AR, CT, TS=0). It is proved that PSO is performed well under UEW conditions. Also it is observed that the PSO is capable of providing the least tolerance under the UEW case [21].

But in this paper, PSO is implemented for two different cases, one with equal weight ages to key parameters (one electrical and one mechanical) and the other with un-equal weight ages to them. Throughout the implementation of PSO, the other parameters like VRY, AR, TS, SRY/CT are assigned with a default value of 0.1. The objective of this work is to consider all the 6 parameters on the whole to obtain the improved performance.

For the two derived sets (set1 and set2) PSO method is applied. The result of PSO has been compared with the graphical method. Among the several electrical and mechanical parameters mentioned, surface resistivity, comparative tracking index and the elongation at break are the key parameters that decide the behavior of the polymer blend for cable applications. If a slight improvement in any parameter is needed by the end user, PSO can help them to find the nearest probable blend ratio.

To validate the results obtained using PSO, GA has been applied for two sets (1 and 2). The results obtained by graphical method and Genetic Algorithm (GA) has been compared with PSO in order to highlight the superiority of PSO. Due to the natural genetic operations, GA would still result in enormous computational effort. It may appear shortcoming of premature/slow convergence [19, 20, 21].

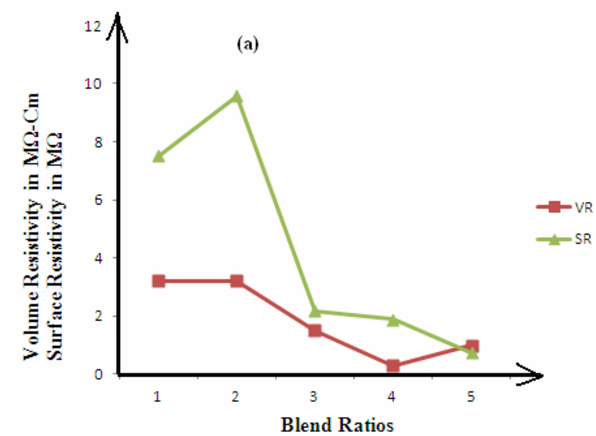
## EXPERIMENTAL

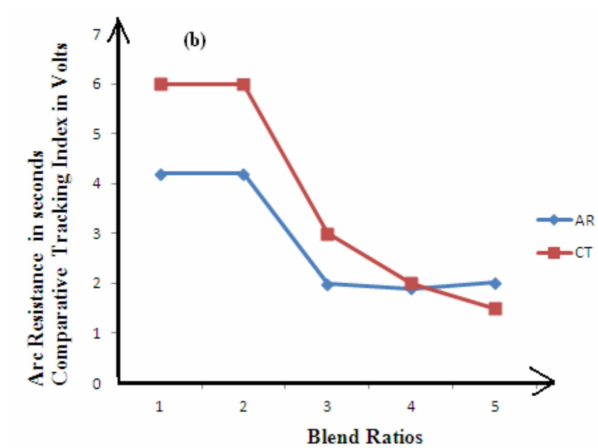
### (a) Blend preparation

The sheets of the blends are prepared with 5 different compositions of EPDM/SR the detailed blend preparation procedure has been given in appendix-I

### (b) Mechanical-electrical characterization

For all the prepared blends of SR-EPDM, the electrical and mechanical parameters are measured as per ASTM and IEC standards. The experimental procedures are given in appendix-II. The Figure-1 depicts the various electrical and mechanical parameters measured for various blends.



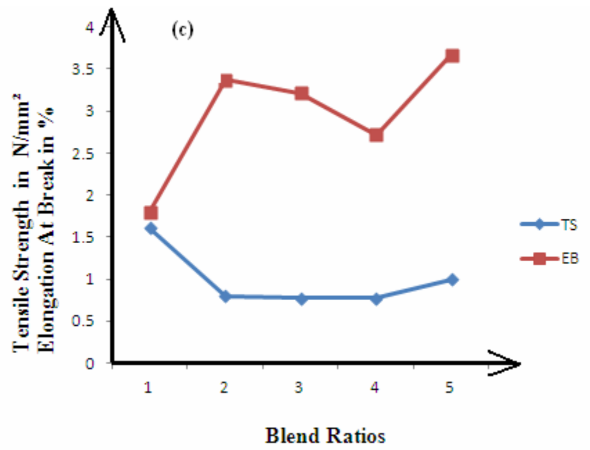



**Figure-1.** Measured electrical/mechanical parameters for different blend ratios.

## OPTIMIZATION METHODOLOGIES FOR DETERMINATION OF OPTIMUM BLEND

### (a) Graphical method

To identify the optimal blend, the required electrical parameters of the different blends are matched against the mechanical parameters individually and the point of intersection gives the approximate optimal blend ratio for a specific application. The similar procedure has been adopted by some authors [7].

But the major drawback of this graphical method is that the accurate composition of blend can not be obtained. Also, if the weightage assigned to each of the parameter varies, then its effect on BR can not be predicted. Also, it is hard to predict the approximate values of parameters for different blend ratios.

### (b) Overview of PSO

Particle swarm optimization (PSO) is an evolutionary computation technique that was originally developed in 1995 by Kennedy and Eberhart. It has been developed through simulation of simplified social models and has been found to be robust for solving non-linear, non- differentiability multiple optimal and multi-objective problems.

The features of the method are as follows:

- The method is based on the researches about swarms such as fish schooling and bird flocking.
- It is based on a simple concept and has high quality solution with stable convergence.
- It was originally developed for non-linear optimization with continuous variables; however it can easily be expanded to treat problems with discrete variables. Therefore it is applicable to find suitable blend for a specific applications.

PSO is an evolutionary technique that does not implement survival of the fittest. Unlike other evolutionary algorithms where an evolutionary operator is manipulated, each individual in the swarm flies in the search space with a velocity which is dynamically adjusted according to its own flying experience and its companions flying experience. The system initially has a population of random solutions. Each potential solution, called a particle, is given a random velocity and is flown through the problem space. The particles have memory and each particle keeps track of its previous best position, called the *pbest* and its corresponding fitness. There exist a number of *pbest* for the respective particles in the swarm and the particle with greatest fitness is called the global best (*gbest*) of the swarm. The basic concept of the PSO method lies in accelerating each particle towards its *pbest* and *gbest* locations, with random weight acceleration at each time step. The modified velocity of each particle can be computed using the current velocity and the distance from *pbest* and *gbest* as given by:

$$V_{id}^{k+1} = W \times V_{id}^{k} + C1 \times rand1 \times (pbest_{id} - x_{id}^{k}) + C2 \times rand2 \times (gbest_{id} - x_{id}^{k}) \quad (1)$$

$V_{id}^{k}$ = current velocity of individual *i* at iteration k such that

$$V_d^{min} \le V_{id}^{k} \le V_d^{max} \quad (2)$$

$V_{id}^{k+1}$ = modified velocity of individual *i*

$x_{id}^{k}$ = current position of individual *i* at iteration *k*

$pbest_i$ = pbest of individual *i*

$gbest_i$ = gbest of the group

$c_1$ and $c_2$ = weighting of the stochastic acceleration that pulls each particle towards

W = inertia weight factor that controls the exploitation and exploration of the search space by dynamically adjusting the velocity. It is computed using:

$$W = W_{max} - \frac{W_{max} - W_{min}}{maxgen} \times iter \quad (3)$$

### (c) Overview of GA

Holland defined the concept of the GA as a metaphor of the Darwinian theory of evolution applied to biology. Implementation of a Genetic Algorithm (GA) begins with a population of random chromosomes. The algorithm then evaluates these structures and allocates reproductive opportunities such that chromosomes which represent a better solution to the problem are given more

VOL. 7, NO. 9, SEPTEMBER 2012 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences



chance to "reproduce". In selecting the best candidates, new fitter offspring are produced and reinserted, and the less fit removed. In using operators such as crossover and mutation the chromosomes exchange their characteristics. The suitability of a solution is typically defined with respect to the current population. GA techniques have a solid theoretical foundation based on the Schema Theorem GAs are often viewed as function optimizers, although the range of problems to which they have been applied is including: pattern discovery, signal processing and training neural networks. GA brings theory of biological evolution into the optimization of parameters through the crossover and mutation operations. It selects the best value of the fitness function and it is reserved. Then it makes up the new cluster.

## REALIZATION OF PROPOSED OBTIMAL BLEND PROBLEM USING PSO

### (a) Problem formulation

The OBP can be formulated as the multi-objective non-linear optimization problem as follows:

$$max_{x\in F}\ f_1(x), f_2(x), \cdots\cdots f_k(x) \quad (4)$$

where

$x \in R^n f_i$

F is the feasible set of problem (4) which is described by the inequalities as follows:

$$F = \{x \in R^n\ f_i : g_i(x) \le 0, i = 0,1,2,\cdots p\} \quad (5)$$

where

$g_i(x)$ is called the constraint function. We denote $f(x) \in R^k$

### (b) Initialization

To implement the PSO, acceleration factors (C1, C2), weighting factor (W) , minimum and maximum inertia weights, $W_{min}$ and $W_{max}$, maximum generation ($gen_{max}$), particle (swarm) size (ps)and termination criteria has to be specified clearly.

### (c) Objective function

A Nonlinear optimization problem can be stated mathematical terms as given in equation (6).
Find

$$F(x) = f_1(x), f_2(x) \cdots\cdots f_k(x) \quad (6)$$

where

$$f(x) = f_1(x) \to VRY, f_2(x) \to SRY, f_3(x) \to AR, f_4(x) \to CT, f_5(x) \to TS, f_6(x) \to EB$$

such that F(X) is minimum or maximum subject to the constraint and bounds are given by equation (7).

$$x_j^l \le x_i \le x_j^u \quad (7)$$

Where F is the objective function to be minimized or maximized, xj's are variables, gj is constraint function, $x_j^l$ and $x_j^u$ are the lower and upper bounds on the variables.

### Case-1

Set-1 represents the optimization problem with maximum weightage assigned to CT and EB. If the maximization of comparative tracking index and elongation at break of a particular polymer blend for a specific application is to be done then the objective function will be:

$$f(x) = f_1(x), f_2(x) \cdots\cdots f_6(x) \quad (8)$$

The objective functions of the set 1 are assigned with the following weightages.

$f_1(x), f_2(x), f_3(x), f_5(x) = 0.1;$
$f_4(x), f_6(x) = 0.3(EW)$
$f_4(x) = 0.35; f_6(x) = 0.25(UEW)$

The constraints for the specific case are as follows.

$1 \le f_4(x) \le 6.5; 0.5 \le f_6(x) \le 4.5$ (lower and upper values of measured parameters).

### Case-2

Set 2 represents the optimization problem with maximum weightage assigned to SRY and EB.

If the maximization of surface resistivity and elongation at break of a particular polymer blend for a specific application is to be done then the objective function is given as:

$$f(x) = f_1(x), f_2(x) \cdots\cdots f_6(x) \quad (9)$$

The objective functions of the set 2 are assigned with the following weightages:

$f_1(x), f_3(x), f_4(x), f_5(x) = 0.1;$

$f_2(x), f_6(x) = 0.3(EW)$

$f_2(x) = 0.2; f_6(x) = 0.4(UEW)$

The constraints for the specific case are as follows.

$0.5 \le f_2(x) \le 10 \ ; \ 0.5 \le f_6(x) \le 4.5$ (lower and upper values of measured parameters).

The proposed PSO algorithm for multi-objective blend ratio optimization of SiR-EP has been compared with GA and graphical method. The efficient operation of PSO requires the careful selection of the C1, C2 and W. The weighting factor (W) will provide a balance between

VOL. 7, NO. 9, SEPTEMBER 2012 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences



the local and the global explorations. The swarm size and maximum number of generations are fixed by trial and error method. The termination of optimization procedure will be attained when 20 iterations are reached.

**(d) PSO algorithm**

a) Initialize the swarm by assigning a random position in the problem hyperspace to each particle.
b) Evaluate the fitness function for each particle.
c) For each individual particle, compare the particle's fitness value with its $p_{best}$. If the current value is better than the $p_{best}$ value, then set this value as the $p_{best}$ and the current particle's position, $x_i$ , as $p_i$.
d) Identify the particle that has the best fitness value. The value of its fitness function is identified as $g_{best}$ and its position as $p_g$.
e) Update the velocities and positions of all the particles using (1) and (2).
f) Repeat steps 2-5 until a stopping criterion is met (e.g., maximum number of iterations or a sufficiently good fitness value).

## VALIDATION OF PSO UING GA

In order to emphasize the advantages of proposed PSO for SBP, GA is also implemented for the above problem. The simulation parameters such as population size, cross-over rate, mutation ratio and number of generations used in GA are listed in Table-1.

**Table-1.** Simulation parameters of PSO and GA.

| GA | | PSO | |
|---|---|---|---|
| Generations | 20 | Iterations | 20 |
| Cross over rate | 0.9 | Wmax | 0.9 |
| Population size | 30 | Number of particles | 30 |
| Mutations ratio | 0.1 | C1 = C2 | 2 |

**Genetic algorithm procedure**

**Step-1:** Read number of inputs, Initialize the parameter with a population of random solutions, such as crossover rate, mutant rate, and numbers of generation.
**Step-2:** Define objective function (a) maximization of surface resistivity and elongation at break.
(b) Maximization of Comparative tracking index and elongation at break identify the parameters.
**Step-3:** Generate initial population.
**Step-4:** Evaluate the population by objective function.
**Step-5:** Test for convergence. If satisfied then stop, else continue.
**Step-6:** Start reproduction process by applying genetic operators: Selection, Crossover and Mutation.
**Step-7:** Evolve new generation. Go to step 3.

## RESULTS

A comparison has been made between the graphical and values obtained using PSO. These values are shortlisted in Tables 2 and 3.

**Table-2.** Comparison of the values obtained by PSO and GA (EW/UEW) with graphical Method for the Set-1 (CT-EB).

| Set 1 | CT=EB=0.3 | | CT=0.35; EB=0.25 | |
|---|---|---|---|---|
| Blend ratios | EW | Tolerance | UEW | Tolerance |
| Graphical | 50/50 | - | 50/50 | - |
| PSO | 61/39 | ±11% | 45/55 | ±5% |
| GA | 61/39 | ±11% | 45/55 | ±5% |

**Table-3.** Comparison of the values obtained by PSO and GA (EW/UEW) with graphical method for the Set-2 (SRY-EB).

| Set 2 | SRY = EB = 0.3 | | SRY = 0.2; EB = 0.4 | |
|---|---|---|---|---|
| Blend Ratios | EW | Tolerance | UEW | Tolerance |
| Graphical | 55/45 | - | 55/45 | - |
| PSO | 44/56 | ±11% | 61/39 | ±6% |
| GA | 44/56 | ±11% | 62/38 | ±7% |

## DISCUSSIONS

From the Table-2 it is seen, with equally assigned weight ages for 2 parameters, tolerance value is ±11%. Also from Table-3, it is observed that with unequally assigned weight ages for 2 parameters in particular set results in the lower tolerance limits. It is inferred that, PSO helps the cable manufacturers to choose the any desired combination of blend ratios based on requirements which is reflected as objective function with required weightages.

VOL. 7, NO. 9, SEPTEMBER 2012 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences



The convergence characteristics of PSO and GA with EW/UEW for the set 1 (CT-EB) are shown in Figures 3(a) and 3(b). The Figures 4 (a) and 4 (b) show the convergence characteristics of PSO and GA for the set 2 (SRY-EB) with EW/UEW. The Figures 5 (a) and 5 (b) depict the mean and standard deviations for the best fitness and worst fitness conditions of PSO and GA for the set 1 (CT-EB) with EW. The Figure-6 shows the comparison of best and worst fitness mean values of PSO and GA for Set 1 (CT-EB)with UEW. The comparison between the best and worst fitness mean values of PSO and GA with EW for the set 2 (SRY-EB) is shown in Figure-7. The Figure-8 gives the comparison between the best and worst fitness standard deviation values of PSO and GA with UEW for the set 2 (SRY-EB).

It is observed that convergence of PSO is quicker than GA and also solution obtained using PSO is better than GA. The PSO method has the lower best fitness and worst fitness mean values than the GA method for both the sets (1 and 3). Hence PSO offers a higher quality solution. Also the standard deviation of the fitness value for 20 trials is very low for the PSO method.

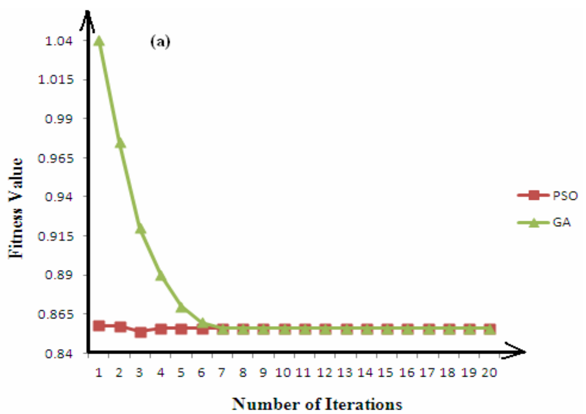



**Figure- 3(a).** Convergence characteristics of PSO and GA for set 1 with EW.

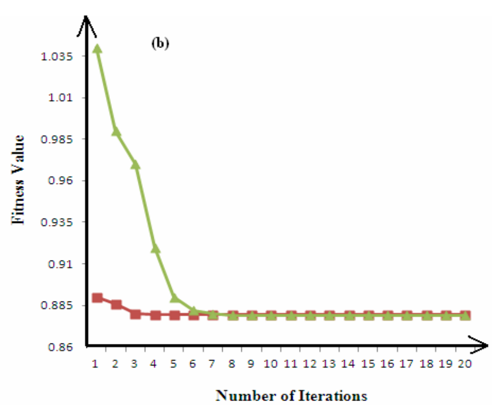



**Figure-3(b).** Convergence characteristics of PSO and GA for set 1 with UEW

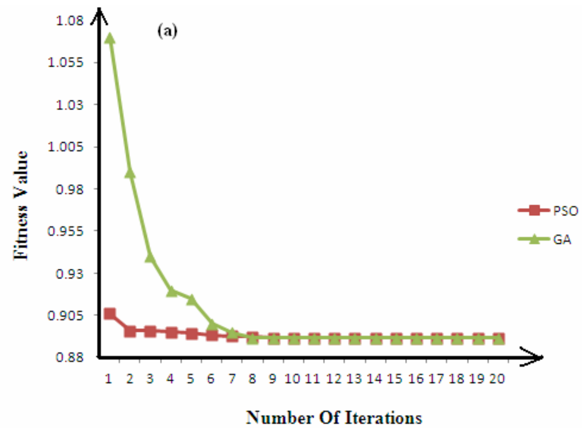



**Figure-4(a).** Convergence characteristics of PSO and GA for set 2 with EW.

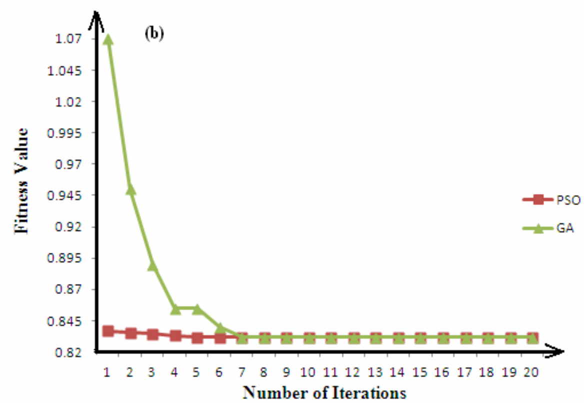
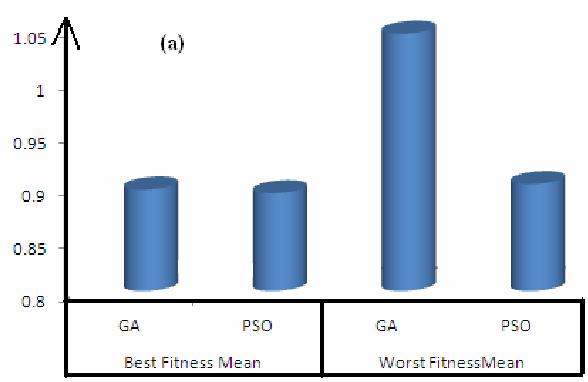



**Figure- 4(b).** Convergence characteristics of PSO and GA for set 2 with UEW.



VOL. 7, NO. 9, SEPTEMBER 2012 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences



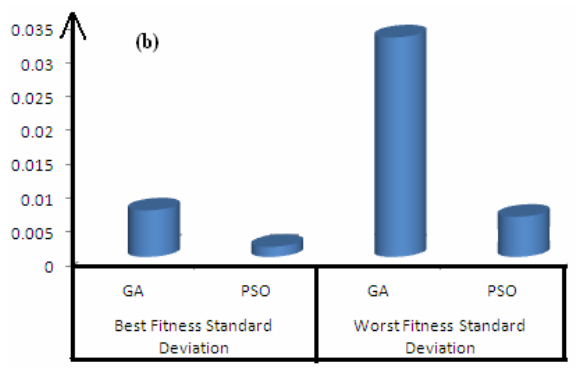



**Figure- 5.** (a) Comparison of best and worst fitness mean values of PSO and GA for Set 1 with EW (b) Comparison of best and worst fitness standard deviations of PSO and GA for Set 1 with EW.

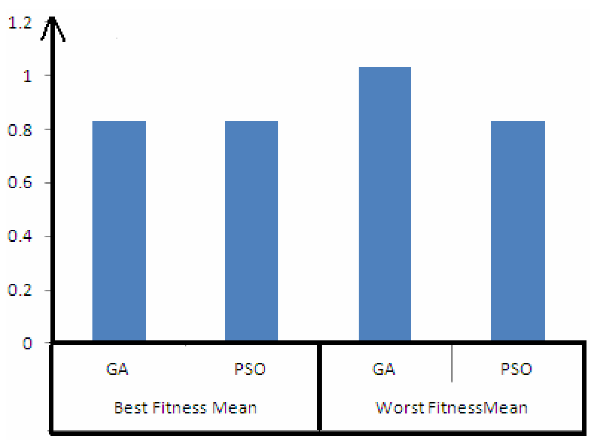



**Figure-6.** Comparison of best and worst fitness mean values of PSO and GA for Set 1 with UEW.


**Figure-7.** Comparison of best and worst fitness mean values of PSO and GA for Set 2 with EW.


**Figure-8.** Comparison of best and worst fitness standard deviations of PSO and GA for Set 2 with UEW.

## CONCLUSIONS

A technique based on particle swarm optimization is developed for finding the optimum blend of SR-EPDM for various cable applications. The proposed method formulates identification OBP which will assist the manufacturers in choosing the OBR for their applications based on the priority level which can be assigned for the various parameters. The feasibility of the proposed method for blend ratio determination is implemented on blends of SiR-EPDM with promising results. The algorithm offers the designers, the flexibility to achieve a compromise between conflicting design objectives like CT, SRY, EB, TS, VRY, and AR. The proposed PSO method has been compared with GA to prove the robustness of PSO. The cable manufacturers can prepare a data base for finding the OBR using PSO. Some tolerance limit can be fixed for each set. The cable end user can post their desired characteristics to manufacturer based upon their requirements. With the help of PSO, cable manufacturer can identify the suitable blend ratio which will suit the requirements.

The identification of the optimal blend is a compromise between various performances criteria, improvements of a particular performance parameter may result in degradation of other parameters. Consequently, the utility has to search for solutions that are feasible with respect to all performance parameters. To deal with this trade off and achieve the desired blend, the multi-objective based PSO seem to be the most suitable approach.

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## APPENDIX

### I. Experimental blend preparation

All the materials (SiR/EPDM) used for this work are commercial one and they are used as received. They are supplied by M/S Joy Rubbers, India. The preparation of SiR/EPDM blends is carried out in a two roll mixing mill (Make Sohail). Certain activators and accelerators are added. The temperature and duration for curing are -140°C and 10 minutes, respectively. The various additives used are given in Table-1. Sheet specimens are made using a hot press machine (Make Zeon).The compounds were sandwiched between the electrically heated plates of Molding machine (Make RNKM) for a period of 3 min and an optimum temperature of 180°C is used for curing the blend.

The sheets of the blends are prepared with 5 different compositions of EPDM/SiR Blend 1 - SiR 90%/ EPDM-10%; Blend 2 - SiR70%/ EPDM-30%; Blend 3-SiR 50% /EPDM 50%; Blend 4-SiR 30%/EPDM 70%; Blend 5-SiR 10%/EPDM 90%

**II -A. Mechanical characterization**

Tensile properties indicate how the material will react to forces being applied in tension. A tensile test is a fundamental mechanical test where a carefully prepared specimen is loaded in a very controlled manner while measuring the applied load and the elongation of the specimen over some distance. Tensile tests are used to determine the modulus of elasticity, elastic limit, elongation, proportional limit, and reduction in area, tensile strength, yield point, yield strength and other tensile properties. Tensile strength is calculated as per ASTM D 412, tensile properties are determined using a universal testing machine (Make-Industrial Lab). The test is carried out on dumb bell specimens at room temperature.

**II -B. Electrical characterization**

The electrical parameters like volume resistivity, surface resistivity and arc resistance are found. The sample surface resistivity is measured with 3 electrode method using a constant DC voltage as per ASTM D257.

The volume and surface resistances are measured using a test cell along with mega ohm meter (Make Prestige Electronics) with a sample size of 10X10X0.3 cm square shaped specimen. The surface resistivity is measured by applying 500V DC between main and guard electrode. The similar procedure is adopted for the volume resistivity also.

Arc resistance is measured using a test set up as per ASTM D 495 (Make SEV). The sample of size 5X5X 0.3 cm is used for this measurement.

Comparative tracking index is measured using an IEC 112, ASTM D3638-85 (Make CEAST). The sample dimensions is 5X5X 0.3 cm. CTI is measured after the application of V ranges from 150-600kV to the test samples.