OPTIMIZING CAM LEVER MECHANISM PERFORMANCE UNDER VARIABLE LOADS USING THE PSO PROCESS

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ABSTRACT

The intelligent collective behavior of certain animals, such schools of fish or flocks of birds, served as inspiration for the population-based stochastic optimization technique called particle swarm optimization (PSO). Many updates and enhancements have been made to it since its 1995 debut. As the technique has been studied further, researchers have published theoretical investigations into parameter effects, developed new applications in diverse domains, generated new versions tailored to varied demands, and given further algorithmic variants. In addition to providing an overview of the PSO's background and development, this page offers a conceptual analysis of the acronym. Next, we will have a look at the current research and practical applications surrounding discrete and parallel PSO algorithms, topological structure, parameter selection, multi-objective optimization, and engineering applications of PSO. The paper concludes with a review of the current state of affairs and some suggestions for further study.

DOI Number: 10.48047/nq.2021.19.8.NQ21169 **NeuroQuantology 2021;19(8):500-504**

1.INTRODUCTION

An evolutionary algorithm for handling continuous optimization problems was suggested by Kennedy and Eberhart (1995) and is known as Particle Swarm Optimization (PSO). Because the PSO algorithm is easy to use and requires minimal tweaks to the parameters, theories surrounding it have advanced substantially over the past 20 years. Numerous successful PSO applications for both single- and multi-objective optimization can be found in the literature. Discrete PSO and DPSO have received a lot of attention, even though PSO was initially developed for continuous optimization problems. Particle trajectories show changes in the likelihood of a coordinate becoming one or zero. In 1997, Kennedy and Eberhart presented a discrete binary version of the particle swarm algorithm. A concise summary of the PSO approach to solving Traveling Salesman Problems (TSP) is given by Clerc. Hendtlass enhanced the PSO algorithm's efficiency by endowing every particle with the ability to handle TSP problems of tiny scale. Pang et al. used fuzzy matrices to depict the particle positions and velocities in the PSO after reinterpreting the operators in the initial PSO formulations. In their reinterpretation of PSO operators, Wang et al. introduced new ideas including the "Swap operator" and the "Swap sequence." They came up with an alternative way to fix the TSP problems. Every one of the DPSO algorithms that have been mentioned so far is considered a real DPSO algorithm because it is evolved from the original PSO. When the population of the city is below 52, these analyses made use of a few benchmark problems from the Traveling Salesman's Problems Library (TSPLIB). To make the problem more complex or to get better results, some researchers combined the DPSO with additional approaches. In order to solve the TSP, Zhong et al. added a mutation factor as a new DPSO parameter. The particle is not an integer permutation but rather an edge collection. Based on the Particle Optimization Algorithm (PSO) and the Chaotic Optimization Technique (COA), Yuan et al. presented a new method for handling TSP issues. By integrating a crossover removal method with an uncertain searching strategy, Shi et al. came up with a new particle swarm optimization method to solve the traveling salesman problem. In order to solve the traveling salesman problem, Machado et al. presented a new hybrid model that integrates particle swarm optimization, genetic algorithms, and quick local search. By combining particle swarm optimization with simulated annealing, Fang et al. improved TSP. Besides the traveling salesman challenge, many scholars thought about additional issues. To address the issue of total weighted tardiness scheduling for a single machine, Anghinol and Paolucci introduced a new discrete particle swarm optimization approach. An improved particle swarm optimization (PSO) method based on rank priority and a twofold justification skill was used to solve the resource-constrained project scheduling problem (RCPSP) by Jia et al. All of the hybrid algorithms discussed above employ additional approaches, making it hard to say that PSO discretization is successful, even if most of them have worked.

2.LITERATURE REVIEW

Shuai Li (2019A new method for solving combinatorial optimization problems called probability mechanism-based particle swarm optimization (PMPSO) is presented in this work. New particles are created by merging the ideal particles of the population with the historical optimal particles of each individual. This method is based on the classical PSO principle. Using a secret probability selection algorithm, our program creates brand-new particles. Adjusting the likelihood of each child element in the next particle generation is done by comparing the elements of each particle to the best particles. The PMPSO algorithm's position, speed, and arithmetic symbols are modified to do this.

Xun Li (2020)

There are certain restrictions on the application and convergence speed of the current particle swarm optimization (PSO) method when it comes to mobile robot path planning. Incorporating a learning component for higher control, a cubic spline interpolation function, a uniform distribution, and an exponential attenuation inertia weight, this work presents an enhanced PSO integration technique based on fresh information. In terms of performance, our improved PSO (IPSO) beats out four previously published path planning algorithms while using fewer iteration steps than competing standard functions.

Applications of PSO

PSO has found application in various scholarly and business contexts. "Electronic and electronic engineering," "automation control systems," "communication theory," "operations research," "mechanical engineering," "fuel and energy," "medicine," "chemistry," "biology," and many more fields utilize the analytical tool provided by the "Web of Science Core Collection." Optimization issues in electrical and electronic engineering were addressed by researchers using PSO. For electrical distribution networks when the load demand is uncertain, Ganguly et al. introduced a multiobjective planning approach that uses DG. By utilizing heuristic selection and designating leaders or guides, the optimization tool—a variation of MOPSO—discovered nondominated solutions. To solve the EDP of electric power generation, Komsiyah employed Gaussian PSO and the Lagrange multiplier. Feng et al. used orthogonal signal rectification and PSO to detect wound infection and improve the electronic nose's performance. A PSO method was suggested by Peksen et al. to determine the thickness and horizontal and vertical resistivities of layered anisotropic earth models. It is possible to utilize the suggested approach to assess one-dimensional direct current data in anisotropic medium, and the outcomes were encouraging. A novel model for charging electric vehicles (EVs) was put out by Yang et al.

The model was optimized using a PSO approach. Simulation findings suggest that the suggested method has the potential to both reduce operational expenses for the power grid and satisfy the driving demands of EV owners. The lowest expansion cost of the electrical energy transmission system was determined by De Mendonc using heuristic data and PSO. The Garver system and two real systems that are similar from the southeast and south of Brazil were both subjected to the proposed method. Using DPSO, Liu et al. investigated the stability and characteristics of bimetallic nanoparticles based on tetrahexahedral Pt that had high-index facets. In order to create a model of the electrical discharge machining process that could adequately anticipate the output, Aich and Banerjee used support vector machines (SVM). The optimal values for the SVM parameters were determined using PSO. Using soil drilling data and the PSO technique, Chou et al. assessed reservoir grounding system deficiencies, taking into consideration lightning protection performance and improved design. By combining the Gauss-Newton method with the PSO algorithm, they demonstrated that et al. used PSO to study two-phase flows in electrical resistance tomography. Thakral and Bakhshi synthesized novel thiophene-, pyrrole-, and furan-containing binary and ternary copolymers by utilizing PSO, negative factor counting, and the inverse iteration method. Semantic technologies like RDF and SPARQL were the focus of Fister et al.'s optimizer efforts. The fitness of the results dictated the optimal combinations of PSO and the other techniques.

3. METHODOLOGY

Design and Implementation of Optimized PSO (OpPSO)

Parameter tuning is the goal of the PSO optimization. In the method, every single particle globally assesses its own fitness in relation to the whole swarm. A particle's velocity is the most important metric, and it changes depending on which particle is the best in the world. Depending on the particle's speed, its location is also changed. The values of the two random constants R1 and R2 range from 0 to 1. Two further constants, c1 and c2, which are positive weighing factors, define the relative behavior of the particle. Using these standards, we can find the best value, both locally and globally. To get the greatest results and a better TSP solution, use these settings. Put the particle's speed at 5 and the weighting factor at 10 for the best outcomes. Two variables, C1 and C2, are considered. You can choose a speed between -5 and 5. Twenty to one hundred particles and twenty to fifty iterations are possible, depending on the problem set.

Tools and Techniques used to develop Simulation Tool

We mimic the operation of an optimization approach based on Swarm Intelligence by taking symmetric TSP instances as input and displaying the optimal tour length as the basic output. We use basic ACO, hybrid ACO, and our favorite, Optimized ACO (OpACO), to get the job done. The optimal processing time and number of tour iterations from source to destination cities are also displayed in the output. Also provided for statistical significance are the results' means and standard deviations. These are all displayed graphically to indicate the high iteration input and instances. Every one of the three variants of PSO—Basic, Hybrid, and Optimized—shares the same input and output conditions. You can import CSV files into the standard TSP library, TSPLIB. The random generation of an enormous number of input combinations is also included. Below you will see the technical prerequisites for creating a simulation tool that can optimize swarm intelligence algorithms. The fundamental setup of the modeling program is illustrated in Figure 4.7.

4.RESULTSAND DISCUSSION

Table:PSOperformancefor bay 29data set

Dataset:bayg29 Iteration=20Number of Particle=30,30,20										
Parameters: Velocity(V)=5InertiaWeight= 10										
	1	2	3	4	5	6	7	8	9	10
Basic	31	31	36	36	36	36	42	42	42	42
Hybrid	18	18	18	18	18	18	44	44	44	44
Optimized	**17**	**17**	**16**	**16**	**16**	**16**	**25**	**25**	**25**	**25**
	11	12	13	14	15	16	17	18	19	20
Basic	42	42	47	47	47	47	53	53	53	53
Hybrid	44	45	45	45	45	45	45	45	45	45
Optimized	**25**	**26**	**28**	**28**	**28**	**28**	**28**	**28**	**28**	**28**

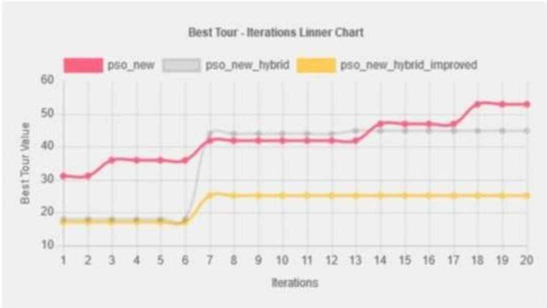

Figure:PSOperformancesforvelocitychangeforbayg29 dataset

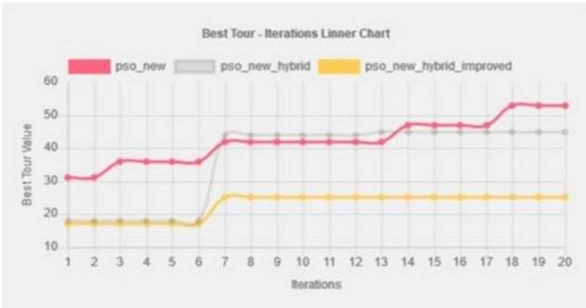

Figure: PSOtimeperformancesforbayg29dataset

Figure: PSOperformancesforOliver30dataset

You can see the outcomes of the PSO algorithm running on the famous Oliver 30 dataset up there in the figures. Compared to the other two algorithms, the fundamental algorithm has a shorter execution time.

Table:PSO besttourresultsforgr24 dataset

Dataset: gr24.csvIteration=20										
PSO Particle =10,VelocityV =5,X =10										
	1	2	3	4	5	6	7	8	9	10
Basic	2817	2817	2817	2817	2817	2817	2817	2817	2817	2817
Hybrid	2342	2342	2342	2342	2342	2342	2342	2342	2349	2349
Optimized	**2289**	**2289**	**2289**	**2289**	**2289**	**2289**	**2289**	**2289**	**2346**	**2346**
	11	12	13	14	15	16	17	18	19	20
Basic	2817	2817	2817	2817	2817	2817	2817	2975	3015	3212
Hybrid	**2349**	**2349**	**2349**	**2349**	**2349**	**2349**	**2349**	**2349**	**2349**	**2349**
Optimized	2352	2352	2352	2352	2473	2473	2473	2550	2685	2685

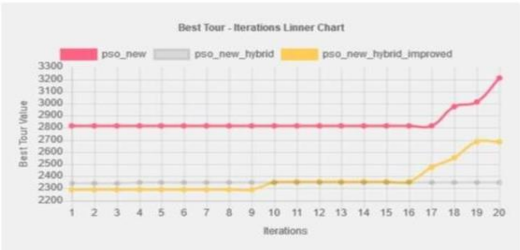

Figure: PSObesttourchartforgr24dataset

The graphic shows the results from the PSOongr24 dataset.While both basic and hybrid PSO hit a wall, optimized PSO continues to show promise. Compared to the other two approaches, processing the dataset using simple PSO is faster.

5.CONCLUSION

There are further engineering problems that the PSO method can solve. The first one concerns the fuel element's spacer grid, while the second one seeks to maximize the cogeneration system's cost-effectiveness. Both cases validated the reliability of the PSO technique with acceptable results. Our in-depth analysis of the most stable carbon-dependent tiny clusters proves that our suggested PSO method works. The existing machine system offers a large future search area dependent only on speed and location, and it is both more advanced and cheaper than previous systems. In order to consistently and efficiently find global minimum energy structures inside a predefined multidimensional search area, our suggested methods provide a fresh viewpoint. With few assumptions, such as symmetry constraints and externally imposed variables like temperature, pressure, etc., PSO implementation is excellent. It eventually settles on one design that can be balanced correctly after Gaussian optimization and is obviously a global minimum energy arrangement. Obtaining a global minimum or a global minimum structure is made easier with the PSO, an easy post-processing procedure. A simple and current computational strategy was used to minimize iteration measures and attain the best global configurations for small carbon clusters with accurate energy values.

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