Chapter 11
Different Applications of PSO

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Abstract Particle swarm optimization (PSO) is an evolutionary optimization algorithm. PSO is a robust and well researched optimization technique. There are a large number of applications of PSO. "Applications of PSO" chapter tries to present a classified literature review for the applications of PSO in different fields. The applications are classified into different sections based on the area of implementation.

The chapter also presents a table with references to multiple other applications over and above those covered in the chapter. References of some largely cited review papers dealing with the applications of PSO are also mentioned at the end of the chapter.

Keywords Particle swarm optimization · Evolutionary algorithms · Application of PSO

11.1 Introduction

Optimization is a part of our daily life where we want to optimize each and every task. We want to optimize our travel plans, our monetary spending, our time and resources, and what not. In reality, we solve these problems by our own conscience, our past experiences, and the experiences of our known ones. If these problems can be converted into a model, then these problems can also be solved through an optimization technique.

What is optimization? In simple words, optimization is making the best use of available situation or resources. In reality, we can only process some of the available solutions that we know or can think of. But there are multiple optimization problems which have a lot of possible solutions which we, as humans, cannot analyze. This

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B. A. Mercangöz (ed.), *Applying Particle Swarm Optimization*, International Series in Operations Research & Management Science 306,
https://doi.org/10.1007/978-3-030-70281-6_11

happens because of a lot of possible combinations between the input variables. Just to get an idea, let us assume that if there are three input variables and each variable can have four different allowable values, then the number of possible solutions will be 64. If these numbers of input variables or their possible values are increased, then the number of possible solutions shall increase by a huge number.

The magnitude of the above-discussed optimization problem increases merely due to the increase in the number of possible solutions. It becomes impossible for a human to evaluate these optimization problems for all the possible solutions. Thus, we need methods to solve such optimization problems.

Evolutionary-based optimization techniques provide very simple and robust methods to solve these problems while providing the advantage of consuming less time. One of such evolutionary optimization technique is particle swarm optimization (PSO). PSO was introduced in 1995 and has been developed to perform better and better over a period of years. The same has been covered in earlier chapters of the book.

In this chapter, we shall look into various applications of PSO and its variants in different fields like engineering, medical, etc. This book itself covers an application of PSO into portfolio optimization. PSO and its applications have a huge number of publications, and it is not possible to include all of them. The chapter is divided into different sections based on the field of applications.

Since the numbers of references for some of the applications are so numerous, that all cannot be referred to; thus, one reference per application has been cited. The total number of applications has been limited to 40. Some of the review papers are cited at the end of the chapter for the benefit of the readers.

11.2 Electrical Engineering

Electrical engineering has a large number of PSO applications.

11.2.1 Reactive Power Optimization

In reactive power optimization problem, the objective is to reduce the total amount of current flowing in the transmission system. Various inputs considered for this problem are voltage magnitude, transformer tap settings, and capacitor bank settings. By optimal selection of input variables, the reactive part of the current, flowing in the transmission system, is reduced (Badar, Umre, & Junghare, 2012).

11.2.2 Load Forecasting

A very important part of job in a power system engineer's work life is the prediction of load in the future. The prediction of load is done for long term (some years), medium term (some months), and short term (some days). PSO is used in combination of various methods like support vector machines (SVM), wavelets, etc. to predict load characteristics for short term. In (Huang, Huang, & Wang, 2005), short-term load forecasting is done using PSO along with autoregressive-moving-average model with exogenous inputs (ARMAX) model. Akaike's final prediction error (FPE) and loss function represent the objective function for the problem discussed. The basic aim is to reduce the error in the prediction process.

11.2.3 Maximum Power Point Tracking in Photovoltaic System

The power generated by the solar panel is adjusted to be maximum for the given condition by tracking the graphs representing the relations between voltage and power and voltage and current. PSO is found to give faster results with lesser oscillations and optimal results in different conditions (Ishaque, Salam, Amjad, & Mekhilef, 2012).

11.2.4 Proportional-Integral-Derivative (PID) Controller

PID controllers are used for various control applications in electrical engineering and other fields. The optimal operation of PID controller is obtained through proper tuning of its parameters, namely, K_p, K_i, and K_d. In (Solihin, Tack, & Kean, 2011), PID controller is used to control the working of a DC motor.

11.2.5 Phasor Measurement Unit (PMU) Placement

Phasor measurement units are a very important part of measuring instruments being utilized in the modern-day electrical systems. Their placement is limited with less number of PMUs being utilized while covering the whole system (Ahmadi, Alinejad-Beromi, & Moradi, 2011).

11.2.6 Economic Dispatch

One of the long-term applications of PSO in electrical engineering is the problem of economic dispatch. This problem tries to find the power plants that should supply power at a given time and how much power each plant should generate. In

(Al Bahrani & Patra, 2017), this problem is applied to modern smart grid conditions with new constraints.

11.2.7 Home Energy Management System

Home energy management is a very important field of research. It takes into account the renewable energy sources, energy storage systems, appliances (controllable and uncontrollable), tariff rates, and many other factors to reduce the cost of energy bills for a home. PSO is applied for reduction in energy costs of a home in (Pedrasa, Spooner, & MacGill, 2010). The home energy management systems usually apply demand response techniques like peak shaving, load scheduling, etc. to achieve these goals.

11.2.8 State Estimation

In an electrical system, there are numerous measurements which are taken and transmitted every second. There are different reasons due to which this measured data may contain uncertainties or noise. State estimation is applied for the estimation of power system variables through the identification of errors. In (Tungadio, Numbi, Siti, & Jimoh, 2015), state estimation is performed using PSO through two objective functions of weighted least square and weighted least absolute value.

11.2.9 Congestion Management

In electrical systems, the power is transmitted from the generating stations to the loads through transmission lines. It is necessary to follow the power transfer limits of the transmission lines. When high power flows through transmission lines, congestion happens. To avoid such situations, congestion management is required. In (Kamaraj, 2011), congestion management is used for pool-based electricity market through PSO. The security constraints considered are line loading and voltages of buses. The method is applied to two standard systems.

11.2.10 Induction Cooker Design

PSO is applied for induction heating design in (Hosseini, Kashtiban, & Alizadeh, 2006). Finite element method is applied alongside PSO to get optimal design. The objective is to minimize the cost as a function of leakage flux and electromagnetic forces of induction heating winding. The parameters considered are DC voltage source, output power, switching frequency, and load resistance and inductance.

11.3 Electronics Engineering

11.3.1 Swarm Robots

PSO finds a very interesting application of searching a given target through a swarm of robots in (Hereford, 2006). PSO eliminates the requirement of having a central leader for coordinating the movement of the robots and is able to find the target in lesser time.

11.3.2 Antenna Design

PSO has been used to optimize antenna design for quite a long time now. In (Robinson & Rahmat-Samii, 2004), PSO is used to design a horn antenna. The antenna design is applied for different types of walls. The simulation output computes beam width, weight, return loss, and peak cross-polarization. There are large numbers of publications using PSO on antenna design optimization problem.

11.3.3 Channel Allocation

In communications, it is very necessary that high bandwidth, absence of delay, and channel availability are provided to users for better quality of service. In (Scott-Hayward & Garcia-Palacios, 2014), PSO is used for multiple application resource allocation. The objective function is based on utility function of channel time allocation for video on demand and Internet protocol television.

11.3.4 Filter Design

PSO has been applied for electronic filters in a large number of research works. In (Krusienski & Jenkins, 2004), PSO is applied on infinite impulse response filters. The mean squared error between the output of unknown system and adaptive filter is related to the cost function which acts as an objective function for the given problem.

11.3.5 Very-Large-Scale Integration (VLSI) Routing

Very-large-scale integration is used to create integrated circuits through the combination of a large number of transistors on a single chip. For such circuits, it is very important to optimize the wire lengths to limit the power delay. Rectilinear Steiner minimal tree is used to obtain the cost of such a circuit. PSO solves this problem in (Khan, Laha, & Sarkar, 2013) with approximately 20% reduction in the cost/length of wire.

11.3.6 Wireless Sensor Network

In wireless sensor network, allocation of workload for each task to proper nodes efficiently is termed as task allocation (Yang, Zhang, Ling, Pan, & Sun, 2013). The constraints for the problem are taken as task workload and connectivity. The fitness function includes time, energy, and lifetime components. The problem has been solved through many different considerations and constraints in the research publications.

11.4 Mechanical Engineering

11.4.1 Machinery Fault Detection

Machines are a very important part of our lives, without which nothing would move and these machines need bearing to run properly. PSO is used to obtain optimal input features for classifiers like SVM or artificial neural network (ANN) while finding machine bearing faults (Samanta & Nataraj, 2009).

11.4.2 Cell Formation

Formation of cells in the manufacturing of machine parts is an important step for optimal process implementation. PSO is used to reduce the setup time and travel of parts in between different cells in (Anvari, Mehrabad, & Barzinpour, 2010). A number of problems are solved to prove the performance of PSO. A similar problem for placement of inventory is handled in (Hochmuth, Lassig, & Thiem, 2011).

11.4.3 Injection Molding

Injection molding is a process of making parts by injecting molten material into a mold. In (Bensingh, Machavaram, Boopathy, & Jebaraj, 2019), PSO is used to predict optimal process parameters, and the whole problem is solved through ANN and PSO.

11.4.4 Milling

Milling is similar to metal cutting having an objective of obtaining optimal surface roughness at micro level and economic performance at macro level. In (Pare, Agnihotri, & Krishna, 2011), surface roughness is optimized, while cutting speed, feed rate, radial rake angle, and depth of cut are taken as input variables.

11.4.5 Multi-hole Extrusion

A Taguchi method and PSO combination is used to find optimal process parameters for a multi-hole extrusion process (Chen, Su, Nian, Lin, & Chen, 2013). The parameters are eccentricity ratio, extrusion velocity, friction coefficient, and billet temperature. Better values of exit tube bending angles and mandrel eccentricity are also obtained. Various softwares are used to verify the results.

11.4.6 Nuclear Power Plant Component Design

To improve the thermal efficiency of a nuclear power plant, modified PSO is proposed in (Liu, Yan, & Wang, 2014). The optimal design is generated for vertical electrical heating pressurizer in reactor coolant system. Optimization variables are primary loop operation pressure, reactor inlet and outlet coolant temperature, and pressurizer inner diameter.

11.5 Computer Engineering

11.5.1 Rule Mining

Association rule mining is a procedure which aims to observe frequently occurring patterns, correlations, or associations from datasets found in various kinds of databases such as relational databases, transactional databases, and other forms of repositories. In (Kuo, Chao, & Chiu, 2011), PSO is applied on standard database to mine association rules for stock selection behavior.

11.5.2 Sentiment Analysis

Artificial intelligence has been developing at a very fast pace. Sentiment analysis is used to analyze the emotions expressed in the text by a human. It is an extremely helpful tool for multiple applications like social networking, product feedback, etc. PSO is used for sentiment analysis in (Gupta, Reddy, Ekbal, et al., 2015) automatic feature selection for aspect term extraction and sentiment classification.

11.5.3 Data Clustering

Clustering is used to partition data based on their similarities. The major problems in this method are compactness and separating data in clusters. In (Armano & Farmani, 2016), clustering is defined as a multi-objective problem, on the basis of connectivity and cohesion. The result gives well-defined, connected, and compact clusters. Around 27 datasets have been implemented in (Armano & Farmani, 2016).

11.5.4 Cloud Computing

Task scheduling is one of the most important requirements in the cloud computing environment. The task scheduling is responsible for efficient working of cloud computing facilities. The parameters to be considered for optimal task scheduling are time, cost, make span, availability, scalability, reliability, throughput, utilization of resources, etc. In (Awad, El-Hefnawy, & Abdel Kader, 2015), account reliability, execution and roundtrip time, make span, transmission time, cost of transmission, and balancing of load between tasks and virtual machine are considered through the implementation of PSO.

11.5.5 Fuzzy Cognitive Maps

Neural networks and fuzzy modeling methodology make up fuzzy cognitive maps, which are used to simulate complex systems. The main objective is to obtain optimal values of fuzzy cognitive map weights so as to get desirable steady-state behavior from the system while following the constraints of the system. In (Petalas, Parsopoulos, & Vrahatis, 2009), PSO is used to find these weights, and it is verified against a number of fuzzy cognitive map applications.

11.5.6 Video-Based Face Recognition

For artificial intelligence systems, it is important to keep learning, especially when the new data becomes available during operations. Classifier systems are applied for the same, and PSO is applied to guide these classifiers in (Connolly, Granger, & Sabourin, 2012). The proposed method is applied on video-based facial recognition through a combination of fuzzy logic and artificial neural networks. PSO is used to generate and evolve diversified pools of classifiers. Real-world video streams are used to assess the method on the basis of classification rate and resources required.

11.6 Others

11.6.1 Traffic Flow Forecasting

A hybrid combination of PSO and support vector regression (SVR) model is used to predict the flow of traffic in (Hu, Yan, Liu, & Wang, 2016). In the traffic forecasting application, PSO is used to optimize the parameters of SVR.

11.6.2 Oil Well Location and Type

For the development of oil and gas fields, it is important to find optimal location and type for the new wells (Onwunalu & Durlofsky, 2010). The objective function evaluates the net present value of a location and type of well, which includes all types of costs including drilling and other costs.

11.6.3 Maintenance and Inventory Management

A novel application of PSO is found in (Samal & Pratihar, 2015) for maintenance and inventory management of spare parts. It tries to optimize the cost related to combined cost of maintenance and for purchase of spare parts. PSO provided results at par with conventional methods.

11.6.4 Vehicle Routing Problem

Vehicle routing problem is an evolving optimization problem, with practical implementation and various versions appearing over a period of years. The input data consists of number of nodes, distance between them, vehicle type, speed, etc. The objective of the problem is to reduce the time of travel while visiting all the nodes and reducing the traveling distance. In (Ai & Kachitvichyanukul, 2009), a vehicle routing problem is solved through modified PSO. In newer versions of the problem, delivery and pickup details of each node are required.

11.6.5 Submission Decision Process

A multi-objective problem is designed around article submission process and solved through PSO in (Adewumi & Popoola, 2018). The objectives are denoted by “C” for the expected number of citations, “P” for the time required from submission to acceptance for a paper, and “R” for the expected number of submissions.

11.6.6 Ship Design

Barebones PSO has been applied to design the ship in (Yao & Han, 2013). The optimization problem has three objective functions, six design variables, and nine inequality constraints. Design variables considered are length, depth, beam, draft, block coefficient, and speed in knots. Objective functions for the problem are minimization of transportation cost and lightship weight and maximization of annual cargo.

11.6.7 Propylene Reactor Application

An industrial process of Ziegler-Natta propylene polymerization in propylene reactors is solved through non-linear dynamic data reconciliation. PSO is used in (Prata, Schwaab, Lima, & Pinto, 2010) for parameter estimation for error detection. Real and system data for different systems are implemented for steady and dynamic states. The output of PSO leads to a more robust and reliable process. A Welch estimator is used in the process along with non-linear data reconciliation and parameter estimation for detection of error.

11.6.8 Fault Selection in Chemical Process

Fault classification based on a large number of variables in a chemical process industry like Tennessee Eastman process is a tedious task. Authors in (L. Wang &

Yu, 2005) solve this problem having a large amount of data along with irrelevant variables through PSO. SVM is also implemented for classification of fault. The proposed work was executed for around 25 h.

11.6.9 Vapor-Liquid Equilibrium

PSO is used for parameter estimation in (H. Zhang, Kennedy, Rangaiah, & Bonilla-Petriciolet, 2011) while developing mathematical models for analyzing vapor-liquid equilibrium process. These problems are non-linear in nature. The research work is applied on 16 problems. Approaches used in the research work are least squares and error in variable.

11.6.10 Leukemia Detection

Diagnosis of microscopic images can lead to decision support system for the detection of acute lymphoblastic leukemia. PSO is used to identify characteristics that discriminate between healthy and blast cells in (Srisukkham, Zhang, Neoh, Todryk, & Lim, 2017). It applies two PSO methods with different characteristics for better results. Around 180 microscopic images and cross-domain sonar dataset from the UCI Machine Learning Repository are evaluated.

11.6.11 Oil Recovery

Authors in (X. Wang & Qiu, 2013) deal with oil recovery problem from a large heavy oil reservoir. A comparison of three different versions of PSO is presented. Even though many parameters can affect the optimization problem, five parameters selected in this case are injecting fluid temperature, stream and additive gas injection, rate of injection wells, amount of CO_2 in additive gas, and liquid production rate of production wells.

11.6.12 Microscope Autofocusing

A method to autofocus the microscope for keeping micro-objects within the field of the lens is studied in (Bahadur & Mills, 2013). The image should have sharp edges, and the features of the micro-objects should be included in it. The performance of PSO is validated through image variance for sharpness quotient in the presence of noise. Micro-beads are used for experimentation.

A summary of the above applications is presented in Table 11.1.

Table 11.1 Summary of PSO applications

Sr. No.	Topic	References
	Electrical engg	
1	Reactive power optimization	Badar et al. (2012)
2	Load forecasting	Huang et al. (2005)
3	Maximum power point tracking in photo-voltaic system	Ishaque et al. (2012)
4	PID controller	Solihin et al. (2011)
5	PMU placement	Ahmadi et al. (2011)
6	Economic dispatch	Al Bahrani and Patra (2017)
7	Home energy management systems	Pedrasa et al. (2010)
8	State estimation	Tungadio et al. (2015)
9	Congestion management	Kamaraj (2011)
10	Induction cooker design	Hosseini et al. (2006)
	Electronics engg	
1	Swarm robots	Hereford (2006)
2	Antenna design	Robinson and Rahmat-Samii (2004)
3	Channel allocation	Scott-Hayward and Garcia-Palacios (2014)
4	Filter design	Krusienski and Jenkins (2004)
5	VLSI routing	Khan et al. (2013)
6	Wireless sensor network	Yang et al. (2013)
	Mechanical engg	
1 2 3 4 5 6	Machinery fault detection Cell formation Injection molding Milling Multi-hole extrusion Nuclear power plant component design	Samanta and Nataraj (2009) Anvari et al. (2010) Bensingh et al. (2019) Pare et al. (2011) Chen et al. (2013) Liu et al. (2014)
	Computer engg	
1	Rule mining	Kuo et al. (2011)
2	Sentiment analysis	Gupta et al. (2015)
3	Data clustering	Armano and Farmani (2016)
4	Cloud computing	Awad et al. (2015)
5	Fuzzy cognitive maps	Petalas et al. (2009)
6	Video-based face recognition	Connolly et al. (2012)
	Other	
1	Traffic flow forecasting	Hu et al. (2016)
2	Oil well location and type	Onwunalu and Durlofsky (2010)
3	Maintenance and inventory management	Samal and Pratihar (2015), Hochmuth et al. (2011)
4	Vehicle routing problem	Ai and Kachitvichyanukul (2009)
5	Submission decision process	Adewumi and Popoola (2018)
6	Ship design	Yao and Han (2013)
7	Propylene reactor application	Prata et al. (2010)

(continued)

Table 11.1 (continued)

Sr. No.	Topic	References
8	Fault selection in chemical process	Wang and Yu (2005)
9	Vapor-liquid equilibrium	Zhang et al. (2011)
10	Leukemia detection	Srisukkham et al. (2017)
11	Oil recovery	Wang and Qiu (2013)
12	Microscope autofocusing	Bahadur and Mills (2013)

As a last part of the chapter, a collection of review papers dealing with the applications of PSO is listed below Table 11.2.

11.7 Conclusion

Optimization is an ongoing process, whether it is evolution (long term) or any other small process. There are various methods from optimizing a process which may vary from simple observation to very complex mathematical processes.

For problems where large numbers of dimensions are involved along with a complex search space, it becomes impossible for finding an optimal solution through simple classical methods. In such cases, evolutionary algorithms like PSO are utilized. PSO is a robust, dynamic, and adaptive evolutionary optimization technique. The method has been in the research domain for around two and a half decades. It has been applied for optimizing a wide variety of problems. It is one of the most researched optimization techniques. PSO imitates the behavior of flocking animals/human brain to search to optimal results.

PSO is a multidimensional optimization technique which can handle different kinds of problems from various fields. PSO is also capable of implementing different varieties of optimization problems like multi-objective problems, discrete and continuous problems, complex problems, etc.

The operation of PSO is simple and is dependent on two equations: velocity calculation and updating of particle position. PSO has been implemented in a wide variety of fields to solve optimization problems.

This chapter covers PSO applications in the fields of electrical engineering, electronics engineering, mechanical engineering, computer engineering, and a combination of other topics. A large number of references are also cited related to the applications of PSO.

Table 11.2 List of review papers

Sr. No.	Title	Author	Year	References
1	An analysis of publications on particle swarm optimization applications	R. Poli	2008	Poli (2008)
2	Applications of particle swarm optimization in geotechnical engineering: a comprehensive review	M. Hajihassani, D. Jahed Armaghani, R. Kalatehjari	2017	Hajihassani, Armaghani, and Kalatehjari (2018)
3	A comprehensive survey on particle swarm optimization algorithm and its applications	Yudong Zhang, Shuihua Wang, and Genlin Ji	2015	Zhang, Wang, and Ji (2015)
4	Particle swarm optimization: basic concepts, variants and applications in power systems	Yamille del Valle et al.	2008	Del Valle, Venayagamoorthy, Mohagheghi, Hernandez, and Harley (2008)
5	Particle swarm optimization: developments, applications and resources	R.C. Eberhart, Yuhui Shi	2001	Shi and Eberhart (2001)
6	Particle swarm optimization and differential evolution algorithms: technical analysis, applications and hybridization perspectives	Swagatam Das, Ajith Abraham, and Amit Konar	2008	Das, Abraham, and Konar (2008)
7	Particle swarm optimization and intelligence: advances and applications	Konstantinos E. Parsopoulos, Michael N. Vrahatis	2010	Parsopoulos and Vrahatis (2010)
8	Review on applications of particle swarm optimization in solar energy systems	A. H. Elsheikh, M. Abd Elaziz	2018	Elsheikh and Elaziz (2019)
9	Review on the cost optimization of microgrids via particle swarm optimization	Sengthavy Phommixay et al.	2019	Phommixay, Doumbia, and St-Pierre (2020)
10	A review on particle swarm optimization algorithms and their applications to data clustering	Sandeep Rana, Sanjay Jasola, Rajesh Kumar	2010	Rana, Jasola, and Kumar (2011)
11	A review on particle swarm optimization algorithm and its variants to clustering high-dimensional data	Ahmed A. A. Esmin, Rodrigo A. Coelho, Stan Matwin	2015	Esmin, Coelho, and Matwin (2015)
12	A review of particle swarm optimization. Part II: hybridisation, combinatorial, multicriteria and constrained optimization, and indicative applications	Alec Banks, Jonathan Vincent, Chukwudi Anyakoha	2007	Banks, Vincent, and Anyakoha (2008)
13	A survey of particle swarm optimization applications in electric power systems	M. R. AlRashidi, M. E. El-Hawary	2009	AlRashidi and El-Hawary (2008)

(continued)

Table 11.2 (continued)

Sr. No.	Title	Author	Year	References
14	A review of real-world applications of particle swarm optimization algorithm	Michal Pluhacek et al.	2017	Pluhacek, Senkerik, Viktorin, Kadavy, and Zelinka (2017)
15	Particle swarm optimization applications to mechanical engineering-A review	Ninad Kulkarni et al.	2015	Kulkarni et al. (2015)

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