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Optimisation Methods Based on Soft Computing for Improving Power System Stability

Journal of Electrical Systems

Abstract: - In order to keep electrical grids running reliably and efficiently, power system stability is essential. The optimisation of power systems is fraught with complexity and uncertainty, yet soft computing approaches have been shown to be an excellent tool for dealing with these issues. In order to improve the reliability of the power system, this article presents a summary of optimisation techniques that rely on soft computing techniques. , the methods of evolutionary computing, such as particle swarm optimisation (PSO) and genetic algorithms (GA), are discussed. By efficiently searching for optimum solutions in huge solution spaces, these algorithms are used to optimise power system parameters and control techniques. In general, optimisation techniques based on soft computing provide effective and flexible ways to enhance power system stability. These technologies improve grid operation by using swarm intelligence, evolutionary computing, fuzzy logic, and neural networks to tackle the issues of power systems, which are dynamic and unpredictable.

Keywords: Power system stability, Soft computing techniques, Optimization methods, Evolutionary computation, Genetic algorithms (GA).

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Introduction

The reliable and efficient operation of electrical grids relies heavily on power system stability. Ensuring stability is paramount to prevent disruptions, blackouts, and potential damage to equipment. However, the dynamic and complex nature of power systems, coupled with uncertainties arising from varying demand, renewable energy integration, and unforeseen contingencies, pose significant challenges to maintaining stability.

In recent years, soft computing techniques have emerged as promising tools for addressing these challenges in power system optimization. Soft computing encompasses a set of computational methodologies inspired by human decision-making processes, such as neural networks, fuzzy logic, evolutionary computation, and swarm intelligence. These techniques excel in handling imprecision, uncertainty, and non-linearity, making them well-suited for optimizing power system stability.

This paper provides an overview of optimization methods based on soft computing approaches aimed at enhancing power system stability. We focus particularly on evolutionary computation techniques, including genetic algorithms (GA) and particle swarm optimization (PSO), due to their effectiveness in handling large solution spaces and complex optimization problems. Additionally, we explore how these techniques are utilized to optimize power system parameters and control strategies, facilitating the search for optimal solutions to enhance stability.

Furthermore, we highlight the versatility and efficiency of soft computing-based optimization methods in addressing the dynamic and uncertain nature of power systems. By leveraging neural networks, fuzzy logic, evolutionary computation, and swarm intelligence, these methods offer promising avenues for improving power system stability and ensuring reliable grid operation in the face of evolving challenges.

Overall, this paper aims to shed light on the role of soft computing techniques in power system stability optimization, providing insights into their application, benefits, and potential for advancing the resilience and efficiency of electrical grids.

New advancements in soft computing approaches have expanded the scope of automation's potential uses. Such developments would be very useful for process control, an essential application in every sector for managing the many parameters of complex systems. Mathematical models that depict the dynamic behaviour of process control systems form the basis of conventional control theory. Traditional controllers are often unable to compete with intelligent controllers because they are not understandable. Using trustworthy data or an expert's knowledge, soft computing approaches allow for decision-making and learning. Additionally, many uncertainties pertaining to stability and the environment may be handled via soft computing approaches. Various process control case studies are condensed here, and the various domains of soft computing approaches, such as genetic algorithms, fuzzy logic, and hybridization of the two, are examined. According to the findings, soft computing controllers outperform traditional controllers when it comes to error control. In addition, hybrid fuzzy genetic algorithm controllers have outperformed both traditional methods and stand-alone soft computing in terms of error optimisation. New benchmarks in robust representation, modelling paradigms, and optimisation methods for addressing contemporary controller problems have been highlighted by the exponential expansion of soft computing technology. Industrial process controllers have benefited greatly from the advanced techniques made possible by soft computing. When it comes to AI, it is said to be cutting edge. Now that powerful computers are more accessible than ever before, design engineers are using AI to solve a broad variety of intelligent and autonomous control challenges in the actual world. A great deal of progress has been seen in the use of soft computing methods in engineering throughout the last several decades. This approach is essential due to its widespread usage in numerous technical applications. Neuronal theory, fuzzy logic, genetic algorithms, probabilistic reasoning, chaotic systems, and evolutionary computing are the main components of soft computing. In particular, this study takes into account two relatively new methods for system control: fuzzy logic and evolutionary algorithms. As an alternative to the conventional, well-established hard computing paradigms, soft computing approaches have gained popularity. The field of soft computing is only starting to take shape. When compared to hard computing, soft computing approaches use various methodologies that may express notions that are imprecise, ambiguous, or vague.

Power grids are now operating at almost full capacity. Heavy flows, caused by more common generating patterns, are a major source of losses and a danger to the system's stability and security. The end result is an unwelcome rise in the likelihood of power outages of varying intensities. Therefore, everyone agrees that the electrical grid has to be fortified so it can be more self-aware, intelligent, resilient to faults, and controlled both statically and dynamically. A conventional method of fortifying the power grid involves enhancing the electrical transmission system by constructing additional substations, transmission lines, and related equipment. But getting permits, finding suitable sites, and building additional transmission lines is a complex, time-consuming, costly, and sometimes contentious process. Applying state-of-the-art power electronics technology may enhance the utilisation of the current power system. Modern operational issues may be technologically solved with the help of Flexible AC Transmission Systems (FACTS). A number of control tasks, including voltage regulation, power flow management, and system damping, may be accomplished by connecting devices in series or shunt, or a mix of the two. These devices include a STATCOM, SVC, SSSC, and UPFC. This allows for a significant improvement in system performance via regulation of power flows, independent of generation rescheduling or topological changes. In addition, the stability margin is enhanced, losses are minimised, and the thermal limitations are not breached. The power systems engineering community has come to acknowledge the potential advantages of FACTS equipment. The present problem is to maximise the benefit while minimising the expense of these devices. Finding the best spot in the network for the device, determining its ideal size, and optimising its controller settings to get the most out of it in both steady-state and transient operations are the three main parts of this optimisation challenge. Taking all three of these factors into account transforms the issue into a multi-objective optimisation problem, which is notoriously difficult to answer efficiently due to its complicated formulation. One side of the coin is the power system, which is inherently noisy and non-stationary due to its extreme nonlinearity. The intricacy of the control systems makes it challenging to optimise the performance of the FACTS devices, especially when adaptability or intelligent approaches are taken into account. From an optimisation standpoint, it is challenging to identify an appropriate algorithm that can pursue the global optimum with reasonable computational effort due to factors such as multiple local minima, nonconvex feasible regions, discontinuous and discrete domain variables, and multiple objectives.

Placement, size, and control of FACTS devices are only a few examples of the many areas in power systems that need addressing nonlinear, multi-objective optimisation problems. A more effective alternative to analytical approaches for solving these complicated optimisation issues is heuristics-based evolutionary computing, which may avoid the pitfalls of sluggish convergence and the curse of dimensionality. Russell Eberhart and James Kennedy created particle swarm optimisation (PSO) in 1995 as an evolutionary computing method that mimics the cooperative actions of schools of fish and flocks of birds. PSO is based on a multidisciplinary approach that draws from engineering, computer science, social psychology, and artificial life. It employs a "population" of particles that, at specified velocities, traverse the problem's hyperspace. The speeds of the individual particles are randomly modified at each cycle based on the particle's best historical location and the best neighbourhood position. A user-defined fitness function is used to calculate both the particle best and the neighbourhood best. Optimal or nearly-optimal particle mobility is an inevitable byproduct of evolution. PSO has a reputation for efficiently resolving nonlinear optimisation issues on a large scale. It converges to the optimum solution in many instances where most analytical approaches fail to converge, and it is not much impacted by the size and nonlinearity of the issue. Consequently, it may be used to manage, size, and place FACTS devices in power systems optimally. In addition, PSO offers a few benefits over other optimisation methods: (i) it's simple to implement and tweak, (ii) it has good memory capabilities, so it can efficiently search the problem hyperspace, and (iii) it keeps particles diverse, which is more like the ideal social interaction in a community, so it can avoid local minima. Specifically, this study suggested an improved particle swarm optimizer (PSO) that amplifies the benefits already mentioned.

Background On Optimal Allocation Of Facts Devices

There are two sections to the optimisation theory overview: (i) traditional optimisation methods and (ii) ECTs. Linear programming (LP), non-linear programming (NLP), quadratic programming (QP), integer programming (IP), mixed integer programming (MIP), and dynamic programming (DP) are all defined in the first section. Section 2 provides an overview of ECTs, including GA, EP, TS, SA, and PSO, as well as more specific ones like simulated annealing and galactic algorithm. In this part, we will go over the kind of issues that various strategies can handle, as well as the pros and cons of each method. There are three primary categories of optimisation methods used to address the FACTS device optimum allocation problem: (i) classical optimisation algorithms, (ii) technical criterion-based device allocation, and (iii) ECTs.

Methods for solving complex optimization problems

One example of a massive man-made machine is the global electric power system. The components include controllers, active/reactive compensators, transmission lines, switches/relays, synchronous generators, and transformers. An optimisation issue must be solved in order to accomplish various control goals, carry out operation activities, and/or make design choices in this kind of system. Solving the optimisation issue for a nonlinear non-stationary system like this is no easy feat, what with all the potential noise and uncertainty and all the different design and operating limitations. In addition, it is necessary to address the following issues: (i) choosing an optimisation method that is suitable for the problem's nature, (ii) making sure all system constraints are met, and (iii) defining an objective function that is comprehensive but not overly complex [1]. In order to solve optimisation issues under different situations, there are a number of different approaches presented in the literature. Every issue may be reduced to its most basic form:

$$Min \quad f(\underline{x}) : A \rightarrow R$$

Subject to

$$g_i(\underline{x}) \leq 0 \quad i = 1, ..., k$$

$$h_j(\underline{x}) = 0 \quad j = 1, ..., m$$

Various optimisation techniques are categorised according to the goals (cost) function f and the kind of the search space $A \subseteq R^n$. Linear programming (LP) is the simplest method since it just requires linear equality and inequality constraints to define the set A and applies to cases where the goal function f is linear [2]. A notion known as nonlinear programming (NLP) arises when either the goal function or the constraints include nonlinearities [3]. Due to the difficulty of natural language processing, academics have focused on specific scenarios to explore. One scenario that has received a lot of attention is when there is a nonlinear objective function f and all the constraints g and h are linear. This optimisation issue is known as linearly constrained optimisation if the goal function is also linear, and quadratic programming (QP) if it is not. [4]. Depending on the specific kind of local data they need, the numerical algorithms in natural language processing may be categorised. Though higher-order derivatives are theoretically feasible, they are seldom employed in reality due to programming challenges, computational complexity, and memory requirements [4]. The method is called mixed integer programming (MIP) or strictly integer programming (IP) when all or part of the variables cannot be non-integer values and nonlinear circumstances are also included. No efficient generic technique has been found to address the MIP and IP issues, which are notoriously tough. If you have this kind of problem, there are essentially three types of algorithms you can use: (i) exact algorithms, which always find the best solution, but they can take an exponential amount of iterations; (ii) approximation algorithms, which give you a less-than-ideal solution in polynomial time; and (iii) heuristic algorithms, which give you a less-than-ideal solution swiftly but don't guarantee its quality. Most real-world optimisation issues include unknown parameters, in contrast to deterministic optimisation problems which are defined with given parameters. The incorporation of the probability distribution functions of different variables into the issue formulation is a necessary step in stochastic programming models. The technique is known as dynamic programming (DP) when used broadly.There are certain drawbacks to using the DP, even if it has been mathematically shown to produce an optimum solution. Practically speaking, solving the dynamic programming algorithm is almost never possible. As the issue size grows, the computing work required to find even a numerical solution grows exponentially, a phenomenon known as the curse of dimensionality.

Because of these limitations, the answer is a less-than-ideal control structure with few rules for the future [6]. Transitioning from finite horizon to infinite horizon issues, taking into account stochastic effects, model defects, and external perturbations further increases the complexity level. Solutions to the aforementioned difficulties may be found using approaches based on computational intelligence, such as GA, EP, TS, SA, and PSO. To build intelligent techniques, computational intelligence integrates aspects of learning, adaptability, and biological evolution [7]. Global optimisation applications of computational intelligence include GA, EP, TS, SA, and PSO, which are general population-based metaheuristic algorithms [8]. The cost function defines the setting in which the potential solutions to the optimisation issue may be found, similar to how a population of people might be considered. Population evolution follows the iterative application of operators like social communication and cultural learning for swarm intelligence-based approaches or inheritance, mutation, natural selection, and crossover for algorithms influenced by evolutionary biology [9]. Since they don't presume anything about the underlying fitness landscape, evolutionary computation techniques reliably provide good approximations for all kinds of situations. Highly restricted and integer (or mixed integer) optimisation problems are good fits for them, and they are relatively unaffected by issue size and nonlinearity.

Classical optimization methods

The FACTS allocation issue has been addressed in the literature using classical optimisation theory, namely MILP and MINLP. The MILP formulation relies on direct current (DC) power flow, which enables a linear representation of the power system [10]-[12]. We examine the system's performance under steady-state settings by taking into account its maximum loadability [10]-[12] and its total transfer capability (TTC) [10]. In order to solve the MILP issue, Bender's decomposition [12], Gomory cuts [10], and B&B [10] are taken into consideration. According to the MILP approach's last statements, the optimisation process is carried out efficiently. The issue then becomes non-linear, since DC power flow is inappropriate for transient analysis and AC models must be addressed. Deregulated market power prices [13], optimum economic dispatch and transmission losses [16], and security improvement [14], [15] are the primary criteria used to calculate the best allocation of FACTS devices in the MINLP-based formulation. The challenge becomes considerably more complicated when considering security improvement, since the power system may be described in terms of many states: normal, collapse, corrective, and preventative. There are specific probability linked to each of these states since they are the result of random occurrences (failures, topological changes). Furthermore, in order to prevent a voltage collapse, load shedding should be considered as a last resort remedy to ensure the problem's viability. All of the published research on optimisation uses Bender's decomposition, a method that breaks down the original issue into smaller, more manageable pieces. Nevertheless, GA is necessary to assist in the optimisation process when security improvement is being considered due to the intricacy of the issue [14], [15]. A convergence issue in the method might be caused by the size and nonconvexity of the problem, which are dependent on the system parameters, according to the key results of the MINLP formulation.

Sensitivity analysis

A commonly used phrase to describe an analysis that involves comparing the rates of change of two sets of system variables is a sensitivity analysis. Various approaches may be used to conduct the analysis, each tailored to the specific factors and procedures that were used to determine the sensitivities. Firstly, the Lagrange multipliers [24] may be used to determine the sensitivities from a traditional optimisation theory standpoint. These multipliers show how the quantity being optimised changes in relation to the particular constraint variable. Conversely, other performance indices, such as the real power performance index, may be developed from a technical standpoint[17,18,21,22], as various rates of change may be of importance depending on the application. Just one example: this index takes into account the derivatives of the power flow equations in relation to the steady-state model of the FACTS devices. One further index that takes into account the proportion of overload in the system's branches for distinct scenarios and gives each one a chance of occurrence is the single contingency sensitivity index [19]. Optimal allocation of TCSCs in a 10-bus system for transient stability is suggested by a sensitivity analysis based on critical clearing time (CCT) [20]. Where the CCT is at its best is where you'll find the FACTS devices. With the exception of the Lagrange multipliers, all of the indices presented above provide a framework for assessing the effects of FACTS devices on the system. Nevertheless, a thorough assessment of all potential places is necessary to determine the optimal placement for any item. Thus, these approaches fail to adequately address the fundamental issue of how to design and execute a suitable search procedure to circumvent the need for an exhaustive search and the associated computing load. Furthermore, these approaches assess the sensitivity indices separately for every FACTS device. This precludes any attempt to assess the system-wide impact of the many devices now in use.

PARTICLE SWARM OPTIMIZATION (PSO)

The two pillars of the conventional PSO formulation are computer science and social science. Swarm intelligence, which PSO employs, is defined as the ability of a system to generate coherent global functional patterns via the coordinated actions of very simple agents interacting with their immediate surroundings. Hence, PSO's foundational elements are:

Ideals in society: "Human intelligence results from social interaction." So the saying goes. Humans adapt to their environments and find the best patterns of behaviour via analysing, comparing, and mimicking others, as well as learning from their experiences. Further, "culture and cognition are inseparable consequences of human sociality," according to a second vital social principle. When people learn from one another and become closer as a result, a culture is born. As a result of cultural influences, people are able to adopt more flexible habits of behaviour..

- Computational characteristics : The concept of swarm intelligence offers a practical framework for developing adaptive systems. It incorporates the gradual parameterization of logical operators such as AND, OR, and NOT, and is an expansion of evolutionary computing. One such example is PSO, which is both an expansion and a new and possibly significant version of cellular automata (CA). A particle swarm may be seen as a collection of CA cells undergoing multi-dimensional state changes all at once. The following twenty-six computational properties are shared by PSO and CA: (i) All particles (cells) undergo updates simultaneously; (ii) the sole factors influencing each new value are the particle's or cell's previous value and its neighbours; and (iii) all updates adhere to the same set of rules..

Algorithm implementation

(i) formulate an appropriate fitness metric for assessing the overall performance of the population,

(ii) Create a particle vector where each dot stands for a possible optimisation issue solution.,

(iii) define the search space by considering workable solutions and excluding those that aren't, and

(iv) fine-tune the algorithm's parameters (acceleration and inertia constants, for example) to get the best possible results (lower computing effort, higher accuracy, etc.).

Fitness function definition

Determining a fitness function that adequately accounts for the primary goals sought is essential for evaluating the positions of individual particles..

Conclusion

This study has offered a synopsis of optimisation techniques for strengthening power system stability that rely on soft computing techniques. We have investigated how to optimise power systems using methods like swarm intelligence, evolutionary computation, fuzzy logic, and neural networks, all of which deal with the inherent complexity and uncertainty of the situation. To optimise power system characteristics and control tactics, we zeroed in on evolutionary computing methods including particle swarm optimisation (PSO) and genetic algorithms (GA). These methods make it possible to efficiently search through huge solution spaces, which makes it easier to find the best solutions to improve stability.Optimisation techniques based on soft computing provide flexible and effective ways to deal with the unpredictable and ever-changing character of power systems. Electrical grids may be reliably operated by power system operators and engineers by using these strategies to improve grid resilience, reliability, and efficiency.

References

[1] Y. del Valle, G. K. Venayagamoorthy, S. Mohagheghi,, J. C. Hernandez, and R. G. Harley, “Particle Swarm Optimization: Basic Concepts, Variants and Applications in Power System,” IEEE Transactions on Evolutionary Computation, Vol. 12, No.2 pp. 171-195, April, 2008.

[2] A. Schrijver, Theory of linear and integer programming. John Wiley and Sons, New York, 1998. ISBN: 0471982326, 9780471982326.

[3] J. Nocedal and S. J. Wright, Numerical optimization, Springer, New York, 1999. ISBN: 0387987932, 9780387987934.

[4] A. Nemirovski, Lecture notes on optimization IIII (ISyE 6663): convex analysis, nonlinear programming theory and nonlinear programming algorithms, School of Industrial and Systems Engineering, Georgia Institute of Technology, 2006.

[5] D. Bertsimas and J. N. Tsitsiklis, Introduction to linear optimization, Athena Scientific Series in Optimization and Neural Computation, 1997. ISBN: 1886529191, 9781886529199.

[6] D. Bertsekas, Dynamic programming and optimal control, Athena Scientific, Boston, MA, 2000. ISBN: 1886529086, 9781886529083.

[7] T. Bäck, Evolutionary algorithms in theory and practice: evolution strategies, evolutionary programming, genetic algorithms, Oxford University Press, Oxford, 1996. ISBN: 0195099710, 9780195099713.

[8] A.E. Eiben and J.E. Smith, Introduction to evolutionary computing, Springer, 2003. ISBN: 3540401849, 9783540401841.

[9] D. B. Fogel, Evolutionary computation: toward a new philosophy of machine intelligence, IEEE Press, Piscataway, NJ, 1995. ISBN: 0471669512, 9780471669517.

[10] A. Sharma, S. Chanana, S. Parida, "Combined optimal location of FACTS controllers and loadability enhancement in competitive electricity markets using MILP," Proc. of the IEEE Power Engineering Society General Meeting, 2005. Vol. 1, Jun. 2005, pp. 670–677.

[11] F. Lima, F. Galiana, I. Kockar and, J. Munoz, "Phase shifter placement in large- scale systems via mixed integer linear programming," IEEE Transactions on Power Systems, Vol. 18, no. 3, Aug. 2003, pp. 1029-1034.

[12] D. Wanhong, T. Lie, "Optimal compensation of variable series capacitors for improved economic dispatch in power systems," Proc. of the IEEE International Conference on Energy Management and Power Delivery (EMPD) 1995,Vol. 2, Nov. 1995, pp. 732-737.

[13] S. Chanana, A. Kumar, "Effect of optimally located FACTS devices on active and reactive power price in deregulated electricity markets," Proc. of the IEEE Power India Conference, 2006, Apr. 2006, pp.7-14.

[14] N. Yorino, E. El-Araby, H. Sasaki, S. Harada, "A new formulation for FACTS allocation for security enhancement against voltage collapse," IEEE Transactions on Power Systems, Vol. 18, no. 1, Feb. 2003, pp. 3-10.

[15] E. El-Araby, N. Yorino, H. Sasaki, "A comprehensive approach for FACTS devices optimal allocation to mitigate voltage collapse," Proc. of the IEEE Transmission and Distribution Conference and Exhibition 2002: Asia Pacific. Vol. 1, Oct. 2002, pp. 62-67.

[16] E. De Oliveira, J. Marangon Lima, K. De Almeida, "Allocation of FACTS devices in hydrothermal systems," IEEE Transactions on Power Systems, Vol. 15, no. 1, Feb. 2000, pp. 276-282.

[17] S. Singh, A. David, "Congestion management by optimising FACTS device location," Proc. of the IEEE International Conference on Electric Utility Deregulation and Restructuring and Power Technologies (DRPT), 2000. Proceedings. Apr. 2000, pp.23–28.

[18] S. Singh, A. David, "A new approach for placement of FACTS devices in open power markets," IEEE Power Engineering Review, Vol. 21, no. 9, Sept. 2001 pp. 58-60.

[19] Yunqiang Lu, A. Abur, "Static security enhancement via optimal utilization of thyristor-controlled series capacitors," IEEE Transactions on Power Systems, Vol. 17, no. 2, May 2002, pp. 324-329.

[20] R. Shizawa, K. Nishida, T. Ohtaka, S. Iwamoto, "Allocation of TCSC from transient stability viewpoint," Proc. of the IEEE International Conference on Power System Technology (PowerCon) 2004. Vol. 1, Nov. 2004, pp. 216-221.

[21] S. Singh, "Location of FACTS devices for enhancing power systems' security," Proc. of the IEEE 2001 Large Engineering Systems Conference on Power Engineering (LESCOPE '01), Jul. 2001, pp. 162-166.

[22] S. Singh, A. David, “Placement of FACTS devices in open power market,” Proc. of the IEEE 2000 International Conference on Advances in Power System Control, Operation and Management (APSCOM-00), Vol. 1, Nov. 2000, pp. 173-177.

[23] J. Singh, S. Singh, S. Srivastava, “Enhancement of power system security through optimal placement of TCSC and UPFC,” Proc. of the IEEE Power Engineering Society General Meeting, 2007. Jun. 2007, pp. 1–6.

[24] T. Orfanogianni, R. Bacher, “Steady-state optimization in power systems with series FACTS devices,” IEEE Transactions on Power Systems, Vol. 18, no. 1, Feb. 2003, pp.19–26.

[25] H. Wang, F. Swift, M. Li, “Selection of installing locations and feedback signals of FACTS-based stabilisers in multimachine power systems by reduced-order modal analysis,” Proc. of the IEE Generation, Transmission and Distribution, Vol. 144, no. 3, May 1997, pp. 263-269.