Reliability Optimization of Multi-Energy System

Subjects: Engineering, Electrical & Electronic
Contributor: Alessandra Parisio , ZIYAN LIAO

Multi-energy systems refer to a new, unified view of energy systems formed by the coupling of cooling and heating in gas and electricity supplies during the transmission and distribution processes, which has the potential to make energy monitoring, generation, consumption, and maintenance more efficient. Multi-energy systems can take full advantage of the interaction between various forms of energy sources to improve system economics, increase system flexibility, and enhance system reliability.

multi-energy system | reliability evaluation and optimization | energy storage configuration schemes | uncertainty modeling | sequential Monte Carlo simulation | metaheuristic algorithms

1. Introduction

Multi-energy systems refer to a new, unified view of energy systems formed by the coupling of cooling and heating in gas and electricity supplies during the transmission and distribution processes, which has the potential to make energy monitoring, generation, consumption, and maintenance more efficient. Multi-energy systems can take full advantage of the interaction between various forms of energy sources to improve system economics, increase system flexibility, and enhance system reliability. However, due to the complex structure of MES and the enormous components they contain, the failure of a single component could have a significant impact on a multi-energy system's overall operation. Thus, it is critical to assess and improve MES reliability effectively and accurately. Multi-energy system reliability is defined as the extent to which the performance of the components in a bulk system provides the customer with electrical, thermal, and gas energy within agreed criteria [1]. Besides assessing MES reliability, improving it is also essential, as it can enhance MES stability and provide energy to the customers more efficiently [2]. MES reliability can be improved by enhancing its flexibility through the optimized use of energy storage systems, which can compensate for the volatility and the uncertainty of renewable generation, such as wind and PV power generation. Therefore, this study explores how to optimize the energy storage configuration schemes to optimize MES reliability.

2. MES Reliability Assessment Overview

After Roy Billiton introduced reliability assessment analysis [3], a large number of researchers conducted multi-energy system reliability assessments. The vast majority of studies focus on the single coupling system, mainly on electricity and heat, with specific application areas [4]. In Ref. [2], the reliability assessment of an electricity–heat integrated energy system with heat pumps based on a Monte Carlo simulation is proposed. The effects of the CCHP system on energy supply reliability are analyzed in [5], concluding that combining energy supplies can significantly increase overall system reliability. In [6][7] , the natural gas network combined with the power distribution system is modeled for the reliability evaluation. A few studies of power–gas–heat multi-energy systems have been undertaken, based on the reliability assessment of single coupling systems. The authors in [8] assess the reliability of a multi-carrier energy system with varying levels of demand while accounting for the uncertainty of different weather conditions. In [9], a user experience-based reliability evaluation of an electricity–gas–heat MES is defined and reliability indicators from the standpoint of user severity and satisfaction with energy consumption are provided. Although the studies evaluate the system reliability by integrating all of the three energy forms, and the authors in [8] also take into account the weather uncertainty, they do not include in their assessment of integrated energy systems renewable energy and energy storage systems, which are instead considered to be essential components of future sustainable energy grids. Multi-energy system reliability evaluation, considering energy storage devices, is introduced in [10][11][12]. The authors in [10] propose a multi-carrier energy system to assess MES reliability while accounting for the influence of energy storage devices. The authors in [11] propose assessing microgrid reliability with energy storage systems by utilizing a Monte Carlo simulation, which considers multi-energy coupling and grade difference. A reliability evaluation approach is devised in [12] by integrating the FMEA (failure mode and effect analysis) method and Monte Carlo simulation to analyze multi-energy micro-grids' reliability while considering various distinct operational strategies for energy storage devices. An MES integrated with electrical vehicles, which are mobile energy storage systems, has been considered in reliability evaluation. The influence of V2G (vehicle to grid) technology on distribution system reliability is studied in [13], using the 24 h available energy model of electric vehicles. The aforementioned works [10][11][12][13] clearly show the key role storage systems play in supporting MES reliability and flexibility. Based on the findings of these studies, it is essential to consider storage systems in order to optimize MES reliability.

3. MES Reliability Optimization Overview

Since energy storage devices can restore power in the event of a power outage while also storing excess energy, reliability optimization that considers different energy storage configuration schemes is essential to enhance the energy supply reliability. Moreover, the primary goal of MES optimization is to satisfy the customer demand at the lowest possible cost while ensuring the highest system reliability [14]. Thus, a multi-objective method is considered in this work to optimize both system reliability and the cost of relative energy storage system investment and the energy not supplied.

Some researchers have attempted to incorporate the results of reliability evaluations into optimal planning problems based on the reliability evaluation approach. The authors in [14] use a Monte Carlo simulation and particle swarm optimization approach to develop an optimal reliability plan for a composite electric power system. The multi-objective optimization of a grid-connected PV–wind hybrid system, taking into account reliability, economic, and environmental factors, is proposed in [15]. The authors in [16] optimize residential buildings with regard to energy demand while imposing reliability constraints, without considering costs. A standalone renewable energy system for 250 households in India, considering the cost of electricity and reliability, is designed in [17]. An optimal day-ahead dispatch and model of predictive control for energy hubs is explored in [18] for simple energy hub layouts, but without considering the optimal system design. The previous research focused on either single energy system optimization or single objective optimization. The economics and reliability of multi-energy systems are still not co-optimized simultaneously, however, despite both being key aspects that need to be taken into account.

4. Main Contributions

Even though the studies mentioned above are relevant, there are still significant gaps and open challenges:

- The reliability assessment of multi-energy systems primarily focuses on single coupling systems, such as power–heat and power–gas systems, and assessments seldom focus on multi-energy systems that combine all three energy forms of power, heat, and natural gas;
- The established reliability modeling approach is very simplistic, ignoring component uncertainty and time-varying load in real-world situations;
- Most previous works solved the problem as a single optimization problem, with the goal of maximizing reliability or lowering cost as the sole objective, and there is still no detailed investigation of optimal storage system design for multi-energy system reliability.

To address these gaps, a sequential Monte Carlo simulation is adopted to assess and quantify MES reliability, based on well-known performance indicators (e.g., the reliability index, SAIDI), and considering storage devices and PV, as well as wind uncertainties. The Monte Carlo simulation is a mathematical technique for modeling risk or uncertainty in complex large-scale systems, and thus can help simulate their operation by using repeated random sampling from the specific probability distribution of random variables [19]. There are two types of Monte Carlo simulation: non-sequential (or random) Monte Carlo and sequential Monte Carlo (chronological). Sequential Monte Carlo simulation, as opposed to the non-sequential approach, simulates the system states in a chronological sequence. Since an MES is a large-scale, complex, dynamic system, the sequential method is more appropriate for evaluating MES reliability [20]. The Monte Carlo simulation approach is integrated into the problem of optimizing MES reliability, taking economic considerations into account. Thus, a reliability optimization is formulated as a multi-objective problem aiming to maximize MES reliability in a cost-effective manner. The resulting optimization problem is highly complex and nonconvex, with a large number of variables and strongly coupled subsystems. Because of this, solving such an optimization problem using analytical methods, such as interior point and branch-and-bound methods, is extremely hard, and metaheuristics are a more suitable option [21]. Metaheuristic methods, such as genetic algorithms and particle swarm optimization, are widely utilized in the energy system domain to tackle numerous problems [21], which include reliability optimization, economic dispatch, optimal power flow, distribution system reconfiguration, load and generation forecasting, and maintenance scheduling. These are solved using metaheuristic optimization in [22][23][24]. Among them, the Pareto-based MOEA (multi-objective evolutionary algorithms), including NSGA-II, MOPSO, and SPEA2, appear to be the most commonly used. The

Pareto front contains a set of non-dominated solutions from which decision makers can choose their preferred one [21]. Since metaheuristics can address multiple-objective, multiple-solution problems and can calculate high-quality solutions to complicated real-world problems [25], this paper adopts these three methods—NSGA-II, SPEA2, and MOPSO to find out the optimal storage device placement schemes. NSGA-II [26], which is one of the most frequently used genetic algorithms and is based on the crowding distance criterion (the average distance between a given solution and the nearest solution belonging to the Pareto front; individuals with greater crowding distances are reserved for the next generation), has a strong capability to avoid being trapped in a local optimal solution. Moreover, NSGA-II has shown fast and efficient convergence to Pareto solutions. Unlike NSGA-II, SPEA2 [27] uses a different criterion-clustering method, which preserves the characteristics of the nondominated solutions. In high-dimensional objective spaces, SPEA2 appears to outperform NSGA-II. However, NSGA-II has a “broader range” of solutions, and is thus more likely to obtain solutions closer to the Pareto optimal front [27]. The principle and technique of MOPSO [28] are relatively simple compared to the other algorithms. MOPSO is based on the flocking behavior of birds, in which an individual’s movement is influenced by the locations and movements of nearby individuals. MOPSO also exhibits a fast convergent rate; however, it performs worse than genetic algorithms at finding Pareto solutions.

References

1. Kueck, J.D. Measurement Practices for Reliability and Power Quality; Oak Ridge Nat. Lab. (ORNL): Oak Ridge, TN (USA), 2005
2. Shenxi Zhang; Min Wen; Haozhong Cheng; Xiao Hu; Guodong Xu; Reliability evaluation of electricity-heat integrated energy system with heat pump. *CSEE Journal of Power and Energy Systems* **2018**, *4*, 425-433, 10.17775/cseejpes.2018.00320.
3. R. Billinton; S. Jonnavithula; A test system for teaching overall power system reliability assessment. *IEEE Transactions on Power Systems* **1996**, *11*, 1670-1676, 10.1109/59.544626.
4. Jun He; Zhijun Yuan; Xiaoling Yang; Wentao Huang; Yicong Tu; Yi Li; Reliability Modeling and Evaluation of Urban Multi-Energy Systems: A Review of the State of the Art and Future Challenges. *IEEE Access* **2020**, *8*, 98887-98909, 10.1109/access.2020.2996708.
5. Jiang-Jiang Wang; Chao Fu; Kun Yang; Xu-Tao Zhang; Guo-Hua Shi; John Zhai; Reliability and availability analysis of redundant BCHP (building cooling, heating and power) system. *Energy* **2013**, *61*, 531-540, 10.1016/j.energy.2013.09.018.
6. J. Munoz; N. Jimenez-Redondo; J. Perez-Ruiz; J. Barquin; Natural gas network modeling for power systems reliability studies. *2003 IEEE Bologna Power Tech Conference Proceedings,* **2004**, *4*, 8, 10.1109/ptc.2003.1304696.
7. Modassar Chaudry; Jianzhong Wu; Nick Jenkins; A sequential Monte Carlo model of the combined GB gas and electricity network. *Energy Policy* **2013**, *62*, 473-483, 10.1016/j.enpol.201

3.08.011.

8. Milad Zamani Gargari; Reza Ghaffarpour; Reliability evaluation of multi-carrier energy system with different level of demands under various weather situation. *Energy* **2020**, *196*, 117091, 10.1016/j.energy.2020.117091.
9. Zihan Meng; Shouxiang Wang; Qianyu Zhao; Zhijie Zheng; Liang Feng; Reliability evaluation of electricity-gas-heat multi-energy consumption based on user experience. *International Journal of Electrical Power & Energy Systems* **2021**, *130*, 106926, 10.1016/j.ijepes.2021.106926.
10. Gaudenz Koeppel; Göran Andersson; Reliability modeling of multi-carrier energy systems. *Energy* **2009**, *34*, 235-244, 10.1016/j.energy.2008.04.012.
11. Ge, S.; Li, J.; Liu, H.; Wang, Y.; Sun, H.; Lu, Z. Reliability evaluation of microgrid containing energy storage system consid-ering multi-energy coupling and grade difference. Autom. Electr. Power Syst. 2018, 42, 165–173.
12. Shaoyun Ge; Hao Sun; Hong Liu; Jifeng Li; Xu Zhang; Yuchen Cao; Reliability Evaluation of Multi-energy Microgrids: Energy Storage Devices Effects Analysis. *Energy Procedia* **2019**, *158*, 4453-4458, 10.1016/j.egypro.2019.01.769.
13. Ammous, M.; Khater, M.; AlMuhaini, M. Impact of vehicle-to-grid technology on the reliability of distribution systems. In Proceedings of the 9th IEEE-GCC Conference and Exhibition, Manama, Bahrain, 8-11 May 2017; pp.1–6
14. R. Ashok Bakkiyaraj; N. Kumarappan; Optimal reliability planning for a composite electric power system based on Monte Carlo simulation using particle swarm optimization. *International Journal of Electrical Power & Energy Systems* **2013**, *47*, 109-116, 10.1016/j.ijepes.2012.10.055.
15. Shimaa Barakat; Haitham Ibrahim; Adel A. Elbaset; Multi-objective optimization of grid-connected PV-wind hybrid system considering reliability, cost, and environmental aspects. *Sustainable Cities and Society* **2020**, *60*, 102178, 10.1016/j.scs.2020.102178.
16. L. Peruzzi; F. Salata; A. De Lieto Vollaro; The reliability of technological systems with high energy efficiency in residential buildings. *Energy and Buildings* **2014**, *68*, 19-24, 10.1016/j.enbuild.2013.09.027.
17. Amarsingh Kanase-Patil; R.P. Saini; M.P. Sharma; Sizing of integrated renewable energy system based on load profiles and reliability index for the state of Uttarakhand in India. *Renewable Energy* **2011**, *36*, 2809-2821, 10.1016/j.renene.2011.04.022.
18. Arnold, M. On Predictive Control for Coordination in Multi-Carrier Energy Systems. Doctoral Thesis. ETH Zurich, Zurich, Switzerland, February 2011.
19. Raychaudhuri, S. Introduction to Monte Carlo simulation. In Proceedings of the Winter Simulation Conference, Miami, FL, USA. 7-10 December, 2008; 91–100.

20. Billinton, R.; Li, W. A system state transition sampling method for composite system reliability evaluation. IEEE Trans. Power Syst. 1993, 8, 761–770.
21. Gianfranco Chicco; Andrea Mazza; Metaheuristic Optimization of Power and Energy Systems: Underlying Principles and Main Issues of the 'Rush to Heuristics'. *Energies* **2020**, *13*, 5097, 10.3390/en13195097.
22. Lee, K.Y.; El-Sharkawi, M.A. Modern Heuristic Optimization Techniques: Theory and Applications to Power Systems; John Wiley & Sons: Hoboken, NJ, USA. 2008; volume 39.
23. Lee, K.Y.; Vale, Z.A. Applications of Modern Heuristic Optimization Methods in Power and Energy Systems; John Wiley & Sons: Hoboken, NJ, USA. 2020.
24. Gianfranco Chicco; Andrea Mazza; Heuristic optimization of electrical energy systems: Refined metrics to compare the solutions. *Sustainable Energy, Grids and Networks* **2019**, *17*, 100197, 10.1016/j.segan.2019.100197.
25. Paola P. Oteiza; Diego A. Rodríguez; Nélida B. Brignole; Parallel cooperative optimization through hyperheuristics. *Computer Aided Chemical Engineering* **2018**, *44*, 805-810, 10.1016/b978-0-444-64241-7.50129-4.
26. K. Deb; A. Pratap; S. Agarwal; T. Meyarivan; A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation* **2002**, *6*, 182-197, 10.1109/4235.996017 10.1109/4235.996017.
27. Kunkle, D. A Summary and Comparison of Moea Algorithms; Internal Report; College of Computer and Information Science, Northeastern University: 2005.
28. Carlos Coello Coello; Gregorio Toscano-Pulido; M.S. Lechuga; Handling multiple objectives with particle swarm optimization. *IEEE Transactions on Evolutionary Computation* **2004**, *8*, 256-279, 10.1109/tevc.2004.826067.

Retrieved from https://encyclopedia.pub/entry/history/show/44145