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Editorial

Progress of Optimization in Manufacturing Industries and Energy System

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1. Introduction

The manufacturing and energy industry are typical complex large systems which cover a long cycle such as design [1], production chain [2], production or operation [3], after-sales [4], etc. A lot of scholars have shown great concerns for different reasons due to the industry's huge body and the vital role of economic society. Liu et al. [5] selected 31 manufacturing industries, used the stochastic frontier analysis (SFA) method to measure R&D efficiency, and used the Tobit regression method to examine the relationship between direct government subsidies, preferential tax policies and manufacturing R&D efficiency. An innovative islanding detection technique was proposed based on active frequency drift (AFD) and the analysis revealed that the proposed method reduced harmonics by 68% compared to conventional AFD and had a larger chopping factor [6]. A technology with a manufacturing working environment extending underwater was proposed for lowering the cost of installing new submarine pipelines, polluting the ocean less, and improving recycling efficiency [7]. Except for studies on policy, safety and technology, a large number of scholars, researchers and engineers have focused on the optimization problems with the goal of increasing profits and reducing costs, which are beneficial for enhancing market competitiveness to manufacturing industries and the energy system.

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2. Optimization Model

An optimization process follows three steps: modeling, solving, and analyzing. An optimization model [8] is generally shown as Formulas (1)–(4):

$$\min/\max z = f(x) \tag{1}$$

$$\text{s.t.} \quad g_i(x) \leq 0 \quad i = 1, 2, \cdots, m \tag{2}$$

$$h_j(x) = 0 \quad j = 1, 2, \cdots, n \tag{3}$$

$$x \in X \tag{4}$$

where z and $f(x)$ are the objective function and an expression for the objective function; $g_i(x)$ and $h_j(x)$ are an inequality and an equality expression of constraint conditions, respectively. x is a variable vector that represents the solution to an optimization problem and X is the range of variable values. Note x can be continuous, discrete, integer, or mixed, which represent continuous optimization, discrete optimization, integer optimization and hybrid optimization.

3. Solution of Optimization

An optimization problem is essentially used to find a global optimal point (or an area for multiple goals) within the feasible domain. The solving algorithm makes a compromise between accuracy and efficiency in the optimization process. The optimization algorithms are usually categorized as traditional optimization algorithms [9] and the intelligent optimization algorithms [10].

Traditional optimization algorithms are divided into analytical methods and direct search methods. The former obtains the extreme point as the optimization point using a mathematical method after converting constraint conditions into non-constraints such as the relaxation variable. The latter obtains a better goal continuously by direct searching, which includes the simplex method, the gradient descent, Tabu search, etc. Analytical methods cannot distinguish the global optima and the local extremum points due to the limitation of mathematical derivation. Direct search methods can only approach the extreme point due to the limitation of searching step length.

A typical optimization problem in the manufacturing industry is called a workshop, which describes how machine resources are used on the production lines [11,12]. A two-stage hybrid flowshop scheduling problem with identical parallel machines in each stage was addressed. To minimize the makespan of the jobs while considering product quality, Shim et al. formulated mathematical programming, developed two dominance properties for this problem, and proposed three heuristics with the suggested dominance properties to solve the considered problem [13].

In the energy community, a wind–hydrogen integrated multi-time scale energy scheduling model was established to optimize the energy consumption scheduling problem of the system [14].

Intelligent optimization algorithms provide another way to improve search efficiency and accuracy by learning or simulating various optimization behaviors and phenomena in the natural world, which include evolutionary and population algorithms [15–18], nature-inspired algorithms [19], metaheuristic algorithms [20], learning-based algorithms [21], etc. A large number of applications [22–24] show that intelligent methods have the abilities to achieve excellent results, especially for complex optimization, which is difficult for traditional optimization algorithms.

A fault diagnosis method using an enhanced fireworks algorithm (EnFWA) was proposed to train and optimize the deep belief network (DBN) network to obtain the best structure with a successful application of the aviation generator [25].

Mistarihi et al. [26] considered the use of the Moth–Flame Optimization (MFO) algorithm and the Salp Swarm Algorithm (SSA), as well as the Whale Optimization Algorithm (WOA), to provide efficient cluster-head selection decisions. Compared to a reference scheme using the Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol, the simulation results showed that integrating the MFO, SSA or WOA algorithms into WSN clustering protocols could significantly extend the WSN lifetime, which improved the nodes' residual energy, the number of live nodes, the fitness function and the network throughput.

In [27], an adaptive particle swarm optimization with a state-based learning strategy (APSO-SL) was put forward. In APSO-SL, in contrast to using iterations to just the population state, using the population spatial distribution was more intuitive and accurate.

4. Constrain Conditions

Key to the optimization model is the establishment of constraint conditions. The most complex constrain conditions in manufacturing industries and the energy system is the process model, which shows the obeyed laws and the mutual influence between variables. Therefore, some different representations of the causal relationship [28], the generative system [29], the graph theory [30] and so on have been imported to reveal the rules of the process in addition to equality constraints and inequality constraints of traditional optimization models.

Rahman et al. introduced some new logarithm operational laws for intuitionistic fuzzy sets and developed some structure properties with more effectiveness compared with the existing methods from the comparison and sensitivity analysis [31].

Mistarihi et al. conducted an experiment utilizing the DMAIC (define, measure, analyze, improve, and control) and simulation technique and its application in reducing waiting time and enhancing overall system efficiency in Jordan's Princess Rahma hospital's pediatric emergency department. The cycle time of the process was reduced by 73% from the previous value, while simultaneously enhancing the total performance of the emergency department by 83% [32]. Though this successful deployment was explored in a healthcare sector, the idea of changing organization for optimization will have a great heuristic effect on process optimization in the manufacturing industry and the energy system.

5. Data-Driven Optimization and Deep Leaning Methods

Thanks to the wide application of a supervisory control and data acquisition (SCADA) system and a significant improvement in computing power, data-driven optimization methods [33] and machine learning technology [34] are showing great promise.

Typical data-driven optimization is approximate dynamic programming which integrates dynamic programming and reinforcement learning. Much success has been reported in this field [35–37]. Data-driven optimization inevitably involves the problems of observation windows and multi-scale information fusion issues. A multivariate data alignment method [38] was proposed to follow different time scales and different role effects, in which data modeling can comply with a data observation window of physical variables behind the data.

Reference [39] surveys machine learning for big data processing. Deep learning is regarded as an excellent tool for simulating the structure and thinking of the human brain. To effectively manage the quality of iron ore, a deep learning scheme for mining the necessary information in sintered image processing [40] was proposed to replace manual labor and realize intelligent inspection. Experiments showed that the improved semantic segmentation model can effectively segment the sintered surface, achieving 98.01% segmentation accuracy with only a 5.71 MB size.

6. Conclusions

This Special Issue took a glimpse at the expansion of manufacturing and energy systems on optimization technologies. On the basis of traditional optimization frameworks, intelligent optimization technology still holds a dominant position, within which the main research focuses on the improvement in the method itself and its integration with the scene.

Process models of constrain conditions are no longer limited to traditional differential equations. Instead, some non-numerical models such as rule-based and graph theory are introduced into manufacturing and energy systems, which enhances the consistency between theory and practical processes. A feasible approach to overcome difficulties caused by introducing complex process models as the constraint is following a virtual simulation by using the powerful processing power of computers.

Data-driven optimization is still in its early stages. However, it has been showing a rapid trend with the development of artificial intelligence technology. Optimization methods based on multi-scale and different dimensional data fusion have great potential prospects in manufacturing and energy systems.

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References

1. Mourtzis, D. Simulation in the design and operation of manufacturing systems: State of the art and new trends. *Int. J. Prod. Res.* **2020**, *58*, 1927–1949. [CrossRef]
2. Li, G.; Wu, H.; Dai, J. Production Sourcing Strategy for an Apparel Original Brand Manufacturer in the Presence of Technology Spillover. *IEEE Trans. Eng. Manag.* **2023**, *70*, 1283–1294. [CrossRef]
3. Fragapane, G.; Ivanov, D.; Peron, M.; Sgarbossa, F.; Strandhagen, J.O. Increasing flexibility and productivity in Industry 4.0 production networks with autonomous mobile robots and smart intralogistics. *Ann. Oper. Res.* **2022**, *308*, 125–143. [CrossRef]
4. Sana, S.S. Optimum buffer stock during preventive maintenance in an imperfect production system. *Math. Methods Appl. Sci.* **2022**, *45*, 8928–8939. [CrossRef]
5. Liu, Z.; Zhou, X. Can Direct Subsidies or Tax Incentives Improve the R&D Efficiency of the Manufacturing Industry in China? *Processes* **2023**, *11*, 181. [CrossRef]
6. Zhang, S.; Wang, L.; Du, X.; Zhang, R.; Huang, Z.; Duan, S.; Yang, W.; Wang, P.; Zhang, J. Improved Active Islanding Detection Technique with Different Current Injection Waveform. *Processes* **2023**, *11*, 1838. [CrossRef]
7. Gong, H.; Ping, Z.; Zhao, T.; Hou, S.; Zu, F.; Qiu, P.; Qin, J. Research on Contact Anchoring Theory and Contact Optimization of Underwater Pipeline Recovery Tools. *Processes* **2023**, *11*, 3166. [CrossRef]
8. Singh, A. An overview of the optimization modelling applications. *J. Hydrol.* **2012**, *466*, 167–182. [CrossRef]
9. Neumaier, A.; Azmi, B.; Kimiaei, M. An active set method for bound-constrained optimization. *Optim. Methods Softw.* **2024**, 1–25. [CrossRef]
10. Nabaei, A.; Hamian, M.; Parsaei, M.R.; Safdari, R.; Samad-Soltani, T.; Zarrabi, H.; Ghassemi, A. Topologies and performance of intelligent algorithms: A comprehensive review. *Artif. Intell. Rev.* **2018**, *49*, 79–103. [CrossRef]
11. Jiang, B.; Ma, Y.; Chen, L.; Huang, B.; Huang, Y.; Guan, L. A Review on Intelligent Scheduling and Optimization for Flexible Job Shop. *Int. J. Control. Autom. Syst.* **2023**, *21*, 3127–3150. [CrossRef]
12. Liu, Y.; Wang, L.; Wang, X.V.; Xu, X.; Zhang, L. Scheduling in cloud manufacturing: State-of-the-art and research challenges. *Int. J. Prod. Res.* **2019**, *57*, 4854–4879. [CrossRef]
13. Shim, S.-O.; Jeong, B.; Bang, J.-Y.; Park, J. Scheduling Jobs with a Limited Waiting Time Constraint on a Hybrid Flowshop. *Processes* **2023**, *11*, 1846. [CrossRef]
14. Wen, X.; Sun, B.; Gu, B.; Lv, Y. Multi-Time Scale Optimal Scheduling Model of Wind and Hydrogen Integrated Energy System Based on Carbon Trading. *Processes* **2023**, *11*, 344. [CrossRef]
15. Rakshit, P.; Konar, A.; Das, S. Noisy evolutionary optimization algorithms—A comprehensive survey. *Swarm Evol. Comput.* **2017**, *33*, 18–45. [CrossRef]
16. Khan, A.; Shafi, I.; Khawaja, S.G.; de la Torre Díez, I.; Flores, M.A.L.; Galvlán, J.C.; Ashraf, I. Adaptive Filtering: Issues, Challenges, and Best-Fit Solutions Using Particle Swarm Optimization Variants. *Sensors* **2023**, *23*, 7710. [CrossRef]
17. Mullen, R.J.; Monekosso, D.; Barman, S.; Remagnino, P. A review of ant algorithms. *Expert Syst. Appl.* **2009**, *36*, 9608–9617. [CrossRef]
18. Yue, Y.; Cao, L.; Lu, D.; Hu, Z.; Xu, M.; Wang, S.; Li, B.; Ding, H. Review and empirical analysis of sparrow search algorithm. *Artif. Intell. Rev.* **2023**, *56*, 10867–10919. [CrossRef]
19. Abdullahi, M.; Ngadi, M.A.; Dishing, S.I.; Abdulhamid, S.I.M.; Usman, M.J. A survey of symbiotic organisms search algorithms and applications. *Neural Comput. Appl.* **2020**, *32*, 547–566. [CrossRef]
20. Salgotra, R.; Sharma, P.; Raju, S.; gandomi, A.H. A Contemporary Systematic Review on Meta-heuristic Optimization Algorithms with Their MATLAB and Python Code Reference. *Arch. Comput. Methods Eng.* **2024**, *31*, 1749–1822. [CrossRef]
21. Li, W.; Wang, G.-G.; Gandomi, A.H. A Survey of Learning-Based Intelligent Optimization Algorithms. *Arch. Comput. Methods Eng.* **2021**, *28*, 3781–3799. [CrossRef]
22. Wang, K.; Liu, W.; Hong, Y.; Sohan, H.S.; Tong, Y.; Hu, Y.; Zhang, M.; Zhang, J.; Xiang, D.; Fu, H.; et al. An Overview of Technological Parameter Optimization in the Case of Laser Cladding. *Coatings* **2023**, *13*, 496. [CrossRef]
23. Afzal, A.; Buradi, A.; Jilte, R.; Shaik, S.; Kaladgi, A.R.; Arıcı, M.; Lee, C.T.; Nižetić, S. Optimizing the thermal performance of solar energy devices using meta-heuristic algorithms: A critical review. *Renew. Sustain. Energy Rev.* **2023**, *173*, 112903. [CrossRef]
24. Lai, V.; Huang, Y.F.; Koo, C.H.; Ahmed, A.N.; El-Shafie, A. A Review of Reservoir Operation Optimisations: From Traditional Models to Metaheuristic Algorithms. *Arch. Comput. Methods Eng.* **2022**, *29*, 3435–3457. [CrossRef] [PubMed]
25. Yang, Z.; Bao, X.; Zhou, Q.; Yang, J. Composite Fault Diagnosis of Aviation Generator Based on EnFWA-DBN. *Processes* **2023**, *11*, 1577. [CrossRef]
26. Mistarihi, M.Z.; Salameh, H.A.B.; Alsaadi, M.A.; Beyca, O.F.; Heilat, L.; Al-Shobaki, R. Energy-Efficient Bi-Objective Optimization Based on the Moth–Flame Algorithm for Cluster Head Selection in a Wireless Sensor Network. *Processes* **2023**, *11*, 534. [CrossRef]
27. Gao, M.; Yang, X. APSO-SL: An Adaptive Particle Swarm Optimization with State-Based Learning Strategy. *Processes* **2024**, *12*, 400. [CrossRef]
28. Runge, J.; Gerhardus, A.; Varando, G.; Eyring, V.; Camps-Valls, G. Causal inference for time series. *Nat. Rev. Earth Environ.* **2023**, *4*, 487–505. [CrossRef]
29. Bhandari, A.; Tripathy, B.; Adate, A.; Saxena, R.; Gadekallu, T.R. From Beginning to BEGANing: Role of Adversarial Learning in Reshaping Generative Models. *Electronics* **2023**, *12*, 155. [CrossRef]

30. Witthaut, D.; Hellmann, F.; Kurths, J.; Kettemann, S.; Meyer-Ortmanns, H.; Timme, M. Collective nonlinear dynamics and self-organization in decentralized power grids. *Rev. Mod. Phys.* **2022**, *94*, 015005. [CrossRef]
31. Rahman, K.; Hezam, I.M.; Božanić, D.; Puška, A.; Milovančević, M. Some Logarithmic Intuitionistic Fuzzy Einstein Aggregation Operators under Confidence Level. *Processes* **2023**, *11*, 1298. [CrossRef]
32. Mistarihi, M.Z.; Al-Tahat, M.D.; Al-Nimer, S.H. Improving Process Efficiency at Pediatric Hospital Emergency Department Using an Integrated Six-Sigma Simulation Methodology. *Processes* **2023**, *11*, 399. [CrossRef]
33. Kou, H.; Zhang, Y.; Lee, H.P. Dynamic optimization based on quantum computation—A comprehensive review. *Comput. Struct.* **2024**, *292*, 107255. [CrossRef]
34. Gambella, C.; Ghaddar, B.; Naoum-Sawaya, J. Optimization problems for machine learning: A survey. *Eur. J. Oper. Res.* **2021**, *290*, 807–828. [CrossRef]
35. Nian, R.; Liu, J.; Huang, B. A review on reinforcement learning: Introduction and applications in industrial process control. *Comput. Chem. Eng.* **2020**, *139*, 106886. [CrossRef]
36. Buşoniu, L.; De Bruin, T.; Tolić, D.; Kober, J.; Palunko, I. Reinforcement learning for control: Performance, stability, and deep approximators. *Annu. Rev. Control.* **2018**, *46*, 8–28. [CrossRef]
37. Guo, S.; Agarwal, M.; Cooper, C.; Tian, Q.; Gao, R.X.; Grace, W.G.; Guo, Y.B. Machine learning for metal additive manufacturing: Towards a physics-informed data-driven paradigm. *J. Manuf. Syst.* **2022**, *62*, 145–163. [CrossRef]
38. Zhang, D.; Sun, K.; Zhang, S. An Approach to Data Modeling via Temporal and Spatial Alignment. *Processes* **2024**, *12*, 62. [CrossRef]
39. Qiu, J.; Wu, Q.; Ding, G.; Xu, Y.; Feng, S. A survey of machine learning for big data processing. *EURASIP J. Adv. Signal Process.* **2016**, *2016*, 67. [CrossRef]
40. Yang, Y.; Chen, T.; Zhao, L. From Segmentation to Classification: A Deep Learning Scheme for Sintered Surface Images Processing. *Processes* **2024**, *12*, 53. [CrossRef]