A Comparative Smart Computation Algorithm for Economic And Emission Dispatch Optimization of Tanjung Jati Power Plant

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ABSTRACT

This research delves into optimization strategies for enhancing power generation efficiency and reducing costs in PLTU Tanjung Jati. The study explores three computational algorithms for optimization: Grey Wolf Optimization (GWO), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO), focusing on optimizing power generation costs while considering penalty costs and emissions. Through extensive simulations and evaluations, the results indicate that the GWO algorithm achieves the most optimal outcomes in terms of cost optimization, demonstrating fast convergence and lesser simulation time compared to the other algorithms. The research provides valuable insights into selecting optimal algorithms for complex optimization problems like Combined Economic Emission Dispatch (CEED) in power generation systems, ultimately contributing to more efficient and cost-effective power generation.

Keywords: GWO, GA, PSO, Optimization, CEED.

INTRODUCTION

Most electricity generation systems depend on fossil fuel-powered thermal power plants. The usage of fossil fuels in these systems needs to be controlled and reduced. Natural fossil fuel resources are limited and not always easily accessible as their supply is concentrated in a few countries that also limit fuel exports (Shafiee & Topal, 2009). The pollution of the environment due to large emissions of particulate gas pollutants is another motivating factor for researchers to reduce the use of fossil fuels in thermal power plant electricity generation. Despite the development and implementation of various alternatives, such as hydroelectric and nuclear power plants, as well as the latest renewable energy technologies, fossil fuels continue to be the most commonly used materials for electricity generation (Portal, 2016).

Efficient and cost-effective electricity generation systems are key in today's energy landscape. The integration of diverse energy sources like renewables and distributed energy has led to a demand for optimization techniques. Economic dispatch, a crucial aspect of power system optimization, remains a significant challenge in this context (Xiang et al., 2021). Economic dispatch involves allocating electricity generation accurately from various sources to meet the demand for electrical voltage while minimizing overall production costs (Chowdhury & Rahman, 1990). Optimizing economic dispatch involves using mathematical techniques to handle dynamic intricacies and unexpected constraints.

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Research related to optimization methods for solving economic and emission dispatch problems has been conducted using various methods, including conventional methods based on mathematical programming with Lagrange relaxation, lambda iteration, Newton Raphson, interior point methods, minimax weighting, and quadratic programming (Bishe et al., 2011; S.-D. Chen & Chen, 2003; Dhillon et al., 1993; Fan & Zhang, 1998; Shalini & Lakshmi, 2014; Singhal et al., 2014). Classical methods have also been used to solve these problems, offering several advantages. These include not needing to determine specific problem parameters, optimization results that can be mathematically proven, and fast computational processes (Bansal, 2005; Pandian et al., 2011; Papageorgiou & Fraga, 2007).

Genetic algorithms (Ponciroli et al., 2020) was used to solve complex economic dispatch problems. It was stated that with the implementation of new technologies, accurately modelling the dynamics of power plant units for economic dispatch becomes increasingly complex. In the current scenario, the scheduling criteria typically followed may no longer yield optimal fleet configurations. Additionally, many commonly used techniques have limited capabilities in modelling the nonlinear dynamics of specific power plants. When a realistic power system consisting of several dozen generating units is modelled, the optimization problem generated turns out to be computationally intensive for current computing capabilities. The results of Ponciroli's research showed satisfactory accuracy with acceptable computational costs.

In other references (Kalakova et al., 2021), an optimal energy scheduling method for power transmission networks using a new genetic algorithm (nGA) was proposed to solve the dynamic economic dispatch (DED) problem combined with short-term load forecasting (STLF) based on machine learning. The short-term load forecasting (STLF) is put into action through a multilayer artificial neural network to predict daily demand fluctuations. The effectiveness of the energy scheduling model, in conjunction with STLF, was validated using an adapted 30-bus IEEE system utilizing real data sourced from power plants situated in the Ereymentau region, Kazakhstan. Simulation outcomes indicate that the proposed model delivers cost-efficient, dependable, and proficient dynamic energy scheduling within power transmission systems.

The economic dispatch problem in power systems aims to reduce the fuel cost of generator units while meeting various constraints in the power system (Ren, 2020). Genetic algorithms (Genetic Algorithm) are adopted as a solution strategy for the economic dispatch problem in power systems, and penalty functions are used to handle constraint conditions in the economic dispatch problem of power systems. Genetic algorithms (GA) are used to solve the economic dispatch problem in the IEEE-9 power system and provide appropriate simulation results. Simulation results show that genetic algorithms can effectively solve the economic dispatch problem in power systems.

Particle swarm optimization (PSO) was used to solve economic dispatch (ED) problems by considering various constraints, including power output balance, thermal production balance, feasible operating area of cogeneration units, and prohibited operating zones (X. Chen et al., 2020). In PSO, every particle employs a migration operator to adjust its position according to the best outcome, aiding in preventing premature convergence and enhancing solution precision.

Additionally, supplementary techniques are applied to manage system constraints and steer solutions towards viable areas. Evaluating the proposed approach involves testing it on four ED problems of varying sizes. The findings indicate that PSO surpasses sophisticated methods in both accuracy and stability, thus suggesting its potential as a valuable alternative for addressing ED problems.

PSO optimization algorithm (Ping et al., 2020) is also used to solve the economic dispatch (ED) problem in power system areas. The adapted PSO improves both global and local search capabilities by iteratively reducing the Gaussian probability distribution around the learning trend point of each particle. This enhancement addresses the challenges posed by various stages of solving ED optimization problems. Evaluations conducted on three different power systems, characterized by nonlinear features like ramp rate limits and non-smooth cost functions, demonstrate the superior performance of the adapted PSO algorithm over other optimization methods in terms of solution quality, convergence, and robustness.

A new optimization technique for solving the combined emission economic dispatch (CEED) problem by considering transmission losses, valve point loading effects, ramp rate limits, and prohibited operating zones was introduced (Rezaie et al., 2019). The CEED problem, one of the most intricate optimization challenges in power systems, has been addressed using an innovative algorithm named advanced particle swarm optimization (APSO). By incorporating several novel adjustments to the traditional PSO algorithm, APSO demonstrates enhanced accuracy, convergence speed, robustness, and overall effectiveness. The algorithm's performance was evaluated across four test systems featuring 14, 40, 54, and 120 generators, yielding high-quality solutions for the optimization problem at hand.

Traditional centralized ED optimization methods have drawbacks such as slow calculation speed, vulnerability to personal equipment exposure, and considering only a single cost objective. Reference (Yin & Sun, 2022) introduces distributed concepts into multi-objective grey wolf optimization (MOGWO) to mitigate these shortcomings and proposes The Distributed Multi-Objective Grey Wolf Optimizer (DMOGWO) addresses challenges in large-scale multi-area interconnected power systems (LMIPSs) by optimizing sub-problems independently from each area and achieving overall optimization through sharing partial inter-area boundary bus information. Case studies on the 39-bus and 118-bus systems from the IEEE (Institute of Electrical and Electronics Engineers) demonstrate that DMOGWO, compared to centralized optimization, effectively maintains information privacy, yields smaller objective values, and exhibits superior performance when solving multi-objective economic dispatch in LMIPS.

Grey Wolf Optimization with Society-Based (SGWO) was implemented to optimally allocate energy generated by power systems (Hosseini-Hemati et al., 2022). This approach organizes packs of wolves into smaller units, each led by its own alpha. These alpha wolves, in turn, follow the dominant leaders while guiding their respective groups, establishing a social hierarchy within the wolf community. To test the effectiveness of this approach, simulations were carried out for two complex optimization problems, including challenges like Valve-Point Loading Effect (VPLE) and Prohibited Zones (PZ) from PO units, as well as interdependencies

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between heat and power generation from CHP units, and transmission power losses. Additionally, SGWO's performance was assessed across twenty-three standard functions to ensure its stability across different function types and dimensionalities. Comparisons with other methods demonstrate the technique's robustness and superior ability to produce optimal solutions meeting all constraints. Moreover, the research findings indicate that a mere 0.5% reduction in production costs can result in Annual Cost Savings increasing anywhere from $2.6 to $34 million. Furthermore, the proposed method outpaces other algorithms in terms of speed, achieving speeds 13 to 26 times faster.

A description of a computational framework to ensure optimal thermal generation scheduling using a new model-based grey wolf optimization (GWO) technique that aligns with environmentally friendly and sustainable economic operations was also introduced in (Kadali et al., 2020). This scheduling challenge involves optimizing two objectives simultaneously, addressed through a linear interpolation penalty pricing model derived from basic geometric equations. To enhance solution quality within a shorter timeframe, algorithm parameters are substituted with system parameters, facilitating both global and local search processes within feasible regions. Additionally, the algorithm integrates suitable constraint management techniques to ensure stable convergence. The efficacy of this approach is demonstrated using a six-unit thermal system, considering factors like transmission line losses and valve-point loading effects. Research findings indicate that the GWO technique introduces novel feasible solutions for quadratic and non-convex thermal operation models, outperforming previously established methods, as highlighted in comparative analyses.

The primary issue with using fossil fuels in power generation is finding the best balance to reduce fuel use and harmful emissions while managing fuel costs. Economic Dispatch aims to minimize fuel costs by optimizing power generation across units, while Emission Dispatch focuses on reducing harmful emissions. These conflicting goals create a complex multi objective optimization problem called combined economic emission dispatch (CEED), where both objectives are considered together (Rahman et al., 2016).

The Tanjung Jati Power Plant is a power generation facility with an installed capacity of 4 x 710 MW and a Capability Power of 4 x 660 MW. It plays a vital role in supplying electricity to Java, Madura and Bali (JAMALI). If any of the four generators experience a shutdown, it will disrupt the interconnection supply to the entire JAMALI region. This power plant also contributes to government efforts to save on the national budget for electricity supply while benefiting the wider community by ensuring adequate electricity supply continuity. Specific information on the use of optimization techniques at the Tanjung Jati Power Plant is crucial for determining efficiency potential and various savings. Research focusing on optimization techniques for cost and emission optimization, particularly for the Tanjung Jati Power Plant, is needed.

This research aims to explore the potential benefits offered by optimization algorithms in power plant operations. Optimization algorithms are known to enhance efficiency, reduce operational costs, and address environmental issues. The study focuses on evaluating the effectiveness of three different algorithms—Grey Wolf Optimization, Genetic Algorithm, and Particle Swarm Optimization—in achieving a balanced electricity delivery strategy. The research goal is to identify which algorithm can significantly contribute to improving economic efficiency and minimizing environmental impact in the power plant by comparing their performances. Despite the current implementation status at Tanjung Jati, this research serves as an exploration of the potential benefits that advanced optimization algorithms can provide in power plant operations, offering valuable insights for enhancing efficiency and sustainability.

RESEARCH METHOD

The object of this research is the group of generators 4x660 MW at the Tanjung Jati B Power Plant. The equipment used in this research consists of hardware and software. The hardware used is a Laptop with Core i7 specifications and 8GB RAM, while the software used includes Matlab 2019b, Microsoft Excel, and Windows 10 Operating System. The data used in this research is real-time data for 4 generators with a capacity of 660 MW, and the simulation parameters are as follows

Table 1. Simulation Parameters

Parameters	Description	Usage
noP	Number of Population/Particle	global
noV	Number of Variables	global
PD	Load Power	global
PL	Power Losses	global
max_iter / Max_iteration	Maximum Iteration	global
populationSize	Size of Population	GA
chromosomeLength	Chromosome Length	GA
mutationRate	The rate of Mutation	GA
tournamentSize	The size of Tournament	GA
eliteCount	Elitism Size	GA
a	A constant	GWO
wMax	Maximum Inertia Load	PSO
wMin	Minimum Inertia Load	PSO
c1	c1 Constant	PSO
c2	C2 Constant	PSO
xmax	Maximum Position point	PSO
xmin	Minimum Position point	PSO
vmax	Maximum Velocity	PSO
vmin	Minimum Velocity	PSO

The data collection method used is documentation data collection by documenting data from the company that is useful for research. This data includes the minimum and maximum power data of the generators. Data analysis is planned to be conducted after the simulation process using Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Grey Wolf Optimization (GWO). Before the simulation process, it is necessary to determine the objective function that aims to be achieved in this research. *Objective Function* for this research is,

$Minimize: \sum_{i=1}^{N}(FC_i + FE_i)$ (1)

N = generator number,

FC_i = Cost function for generator i,

FE_i = Emission function generator i,

The constraints for objective function are,

$P_{min_i} \geq P_i \leq P_{max_i}$ (2)

$P_{total} = P_D + P_L$ (3)

P_{min_i} = minimum power generated from generator i,

P_i = output power from generator i,

P_{max_i} = maximum power generated from generator i,

P_D = Load Power

P_L = Power Losses

Cost function for PLTU Tanjung Jati is,

$FC\ (P) = a_iP^2 + b_iP + c_i$ (4)

a_i, b_i, c_i = generated power cost coefficient for generator i

Pi = output power from generator i

Emission function for PLTU Tanjung Jati is,

$FE\ (P) = \alpha P^2 + \beta P + \gamma$ (5)

α, β, γ = emission cost coefficient from generator i,

Pi = output power from generator i

The calculation flow for the objective function to be achieved in equation (1) is as follows:

1. Finding the power values for each position within the constraints of equations (2) and (3).
2. Calculating the generation cost for each position based on the power calculated in the first step using equation (4).
3. Calculating the emission cost for each position based on the power calculated in the first step using equation (5).
4. Computing the objective function result for each position using equation (1).

The calculation flow from 1 to 4 will be performed during fitness evaluation for each algorithm with 500 iterations. This calculation flow is necessary as part of the optimization process using three algorithms so that the optimization process can proceed to obtain convergent results.

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RESULTS AND DISCUSSION

The economic emission dispatch using GWO, GA, and PSO for 500 iterations was implemented in MATLAB. The initial parameters set for both algorithms are shown in Table 1. The results are displayed in fitness (cost) vs. iteration, as shown in Figures 1, 2, and 3 for each algorithm. These figures depict the convergence of each algorithm, providing a better understanding of convergence time.

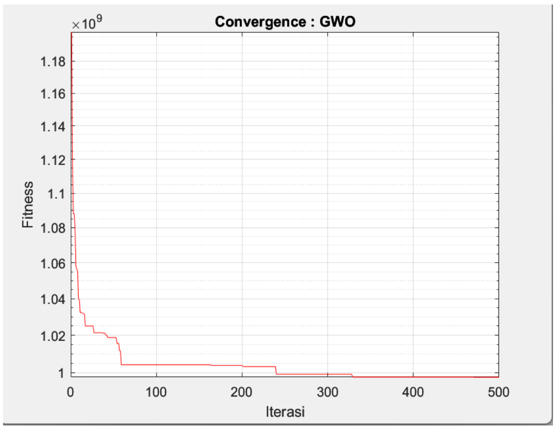

Figure 1. Fitness vs Iteration for GWO Algorithm

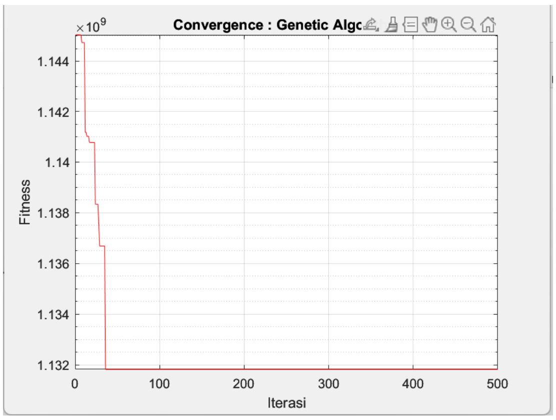

Figure 2. Fitness vs Iteration for Genetic Algorithm

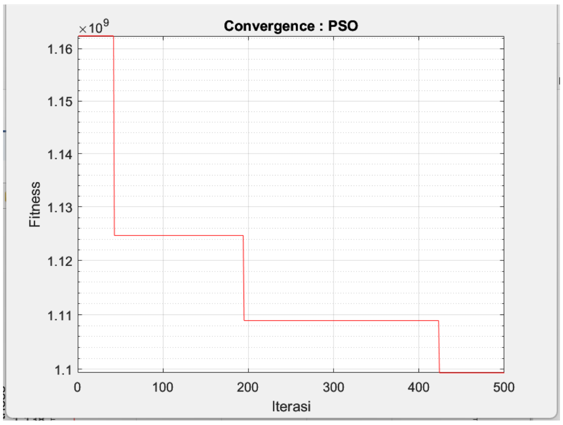

Figure 3. Fitness vs Iteration for PSO Algorithm

The results of the research presented in this paper align with the research objectives. The first objective is to optimize the generation cost and emissions at the Tanjung Jati power plant, while the second objective is to obtain the most optimal algorithm for addressing the CEED problem. Three algorithms were used to achieve the most optimal power generation cost optimization results: Grey Wolf Optimization, Genetic Algorithm, and Particle Swarm Optimization. The optimization results of the objective function can be seen in Table II.

Table 2. Cost Optimization Results

Algorithm	Cost Optimization (Rupiah)
Great Wolf Optimization	997532598.1461
Genetic Algorithm	1131824612.5000
Particle Swarm Optimization	1099393702.7066

The optimization results for power generation costs, considering penalty costs from the GWO algorithm, are as follows: GWO algorithm results in Rp. 997,532,598.15 (61355.14 USD with assumption 1 USD is Rp. 16258.45), GA algorithm results in Rp. 1,131,824,612.5 (69615.02 USD), and PSO algorithm results in Rp. 1,099,393,702.7 (67620.30 USD). Based on these optimization results, the GWO algorithm is the best algorithm for achieving optimal results.

CONCLUSION

The combined economic and emission dispatch of plant generators with respect to fuel and gas emissions was carried out using GWO, GA and PSO in MATLAB. The results demonstrate that GWO outperforms GA and PSO for the combined economic and emission dispatch in terms of achieving lower fuel cost, lower emission, fast convergence, and lesser simulation time. This was validated for both the IEEE 30 bus system and for an independent power plant with simulation and thorough discussion. The work has successfully implemented

GWO, GA, and PSO algorithms for CEED for the same systems. The simulation results are compared and tabulated for different load demands. 2D plots were discussed to highlight the convergence characteristics of GWO, GA and PSO with respect to fitness (Operational Cost) and Iteration. In future studies, the combined dispatch will be made more realistic, by including some other practical constraints like valve point loading, ramp rate limits, prohibited operating zones of generators, transmission line losses etc. The algorithms, GWO, GA and PSO, can be made more efficient by studying and improving their performance parameters.

REFERENCES

Bansal, R. C. (2005). Optimization methods for electric power systems: An overview. *International Journal of Emerging Electric Power Systems*, *2*(1).

Bishe, H., Rahimi-Kian, A., & Esfahani, M. (2011). A Primal-Dual Interior Point Method for Solving Environmental/Economic Power Dispatch Problem. *International Review of Electrical Engineering*, *6*, 1463–1473.

Chen, S.-D., & Chen, J.-F. (2003). A direct Newton–Raphson economic emission dispatch. *International Journal of Electrical Power & Energy Systems*, *25*(5), 411–417. https://doi.org/https://doi.org/10.1016/S0142-0615(02)00075-3

Chen, X., Li, K., Xu, B., & Yang, Z. (2020). Biogeography-based learning particle swarm optimization for combined heat and power economic dispatch problem. *Knowledge-Based Systems*, *208*, 106463. https://doi.org/https://doi.org/10.1016/j.knosys.2020.106463

Chowdhury, B. H., & Rahman, S. (1990). A review of recent advances in economic dispatch. *IEEE Transactions on Power Systems*, *5*(4), 1248–1259.

Dhillon, J. S., Parti, S. C., & Kothari, D. P. (1993). Stochastic economic emission load dispatch. *Electric Power Systems Research*, *26*(3), 179–186. https://doi.org/https://doi.org/10.1016/0378-7796(93)90011-3

Fan, J.-Y., & Zhang, L. (1998). Real-time economic dispatch with line flow and emission constraints using quadratic programming. *IEEE Transactions on Power Systems*, *13*(2), 320–325.

Hosseini-Hemati, S., Derafshi Beigvand, S., Abdi, H., & Rastgou, A. (2022). Society-based Grey Wolf Optimizer for large scale Combined Heat and Power Economic Dispatch problem considering power losses. *Applied Soft Computing*, *117*, 108351. https://doi.org/https://doi.org/10.1016/j.asoc.2021.108351

Kadali, K. S., Loganathan, R., Veerasamy, M., & Jawalker, V. (2020). *Environmentally Sustainable Economic Dispatch Using Grey Wolves Optimization*.

Kalakova, A., Nunna, H. S. V. S. K., Jamwal, P. K., & Doolla, S. (2021). A Novel Genetic Algorithm Based Dynamic Economic Dispatch With Short-Term Load Forecasting. *IEEE Transactions on Industry Applications*, *57*(3), 2972–2982. https://doi.org/10.1109/TIA.2021.3065895

Pandian, S., Thanushkodi, K., Anjana, P. S., Dilesh, D., Kiruthika, B., Ramprabhu, C. S., & Vibinth, A. (2011). *An efficient particle swarm optimization technique to solve combined economic emission dispatch problem*. *54*, 187–192.

Papageorgiou, L. G., & Fraga, E. S. (2007). A mixed integer quadratic programming formulation for the economic dispatch of generators with prohibited operating zones. *Electric Power Systems Research*, *77*(10), 1292–1296. https://doi.org/https://doi.org/10.1016/j.epsr.2006.09.020

Ping, L., Sun, J., & Chen, Q. (2020). Solving Power Economic Dispatch Problem with a Novel Quantum-Behaved Particle Swarm Optimization Algorithm. *Mathematical Problems in Engineering*, *2020*, 9741595. https://doi.org/10.1155/2020/9741595

Ponciroli, R., Stauff, N. E., Ramsey, J., Ganda, F., & Vilim, R. B. (2020). An Improved Genetic Algorithm Approach to the Unit Commitment/Economic Dispatch Problem. *IEEE Transactions on Power Systems*, *35*(5), 4005–4013. https://doi.org/10.1109/TPWRS.2020.2986710

Portal, T. D. (2016). Breakdown of electricity generation by energy source| The shift Project data portal. *TSP-Data-Portal Org: TSP Data Portal*.

Rahman, I., Vasant, P. M., Singh, B. S. M., Abdullah-Al-Wadud, M., & Adnan, N. (2016). Review of recent trends in optimization techniques for plug-in hybrid, and electric vehicle charging infrastructures. *Renewable and Sustainable Energy Reviews*, *58*, 1039–1047. https://doi.org/https://doi.org/10.1016/j.rser.2015.12.353

Ren, Y. (2020). Solving Power System Economic Dispatch Problem Based on Genetic Algorithm. *Journal of Physics: Conference Series*, *1575*(1), 12048. https://doi.org/10.1088/1742-6596/1575/1/012048

Rezaie, H., Abedi, M., Rastegar, S., & Rastegar, H. (2019). Economic emission dispatch using an advanced particle swarm optimization technique. *World Journal of Engineering*, *16*(1), 23–32. https://doi.org/10.1108/WJE-04-2018-0126

Shafiee, S., & Topal, E. (2009). When will fossil fuel reserves be diminished? *Energy Policy*, *37*(1), 181–189. https://doi.org/https://doi.org/10.1016/j.enpol.2008.08.016

Shalini, S. P., & Lakshmi, K. (2014). Solution to Economic Emission Dispatch problem using Lagrangian relaxation method. *2014 International Conference on Green Computing Communication and Electrical Engineering (ICGCCEE)*, 1–6. https://doi.org/10.1109/ICGCCEE.2014.6922314

Singhal, P. K., Naresh, R., Sharma, V., & Kumar, G. (2014). Enhanced lambda iteration algorithm for the solution of large scale economic dispatch problem. *International Conference on Recent Advances and Innovations in Engineering (ICRAIE-2014)*, 1–6.

Xiang, Y., Wu, G., Shen, X., Ma, Y., Gou, J., Xu, W., & Liu, J. (2021). Low-carbon economic dispatch of electricity-gas systems. *Energy*, *226*, 120267. https://doi.org/https://doi.org/10.1016/j.energy.2021.120267

Yin, L., & Sun, Z. (2022). Distributed multi-objective grey wolf optimizer for distributed multi-objective economic dispatch of multi-area interconnected power systems. *Applied Soft Computing*, *117*, 108345. https://doi.org/https://doi.org/10.1016/j.asoc.2021.108345