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Simulated Annealing and Its Applications to Mechanical Engineering: A Review

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ABSTRACT- This work focuses on the significant family of stochastic approaches for global optimization known as simulated annealing (SA), which is based on the key concept of annealing, which describes the cooling of a solid until it reaches the configuration of lowest energy. This paper presents a review of simulated annealing applications meant to solve many problems in the field of mechanical engineering.

KEYWORDS- Simulated Annealing, Optimization, Meta-heuristics, Mechanical Engineering

I. INTRODUCTION

To address the increasing complexity of optimization problems in diverse fields, the most recent advancement in approximate search methods has been the development of meta-heuristics. They use stochastic (rather than deterministic) operators to investigate the design space and direct the search toward optimal designs. In most cases, metaheuristic algorithms are governed by a number of algorithmic parameters. These algorithmic parameters can be altered in order to fine-tune the search technique to the particular optimization problem that is being addressed. The term "control parameters" refers to these particular parameters. Simulated annealing, particle swarm optimization, genetic algorithm, tabu search, black hole algorithm, differential evolution, gravitational search algorithm, evolutionary strategy, ant colony optimization, evolutionary programming, and particle swarm optimization are examples of such approaches.

In the realm of optimization, simulated annealing (SA) was proposed by Kirkpatrick Scott [1] in 1983. The basis for simulated annealing is a work by Metropolis et al. [2]. As a meta-heuristic (a search technique that can find global solutions rather than just local ones), simulated annealing is able to break out of local minima. Its popularity over the past two decades can be attributed to the fact that it is straightforward to implement, converges quickly, and uses hill-climbing strategies to break out of the constraints of local minima. To optimize a multi-parameter model, the popular and easily implemented approach of choice is simulated annealing.

II. SIMULATED ANNEALING

In physical annealing, a crystalline material is first heated. Then it is allowed to cool slowly. It keeps going until the most regular crystal lattice configuration is reached. When the cooling process is allowed to proceed at an adequately slow rate, the final arrangement can produce a solid with an outstanding degree of structural stability. Crystal imperfections are eliminated because this state has the lowest possible lattice energy. This is the process that simulated annealing attempts to mimic.

Using simulated annealing, we can connect this thermodynamic behaviour to the search for global minima in a problem of discrete optimization. At each iteration of the method applied to a discrete optimization problem, the values of two solutions (the current solution and a new solution) are compared. In the pursuit of a global optimum, only solutions that improve on the current state are accepted, while certain non-improving (inferior) options are approved in the hopes of breaking out of a local optimum and finding a better one elsewhere.

Simulated annealing's main algorithmic strength is that it allows for hill-climbing manoeuvres, which are a technique of evading local minima. When the temperature value approaches zero, hill-climbing moves occur less often. The solution distribution that is related with the inhomogeneous Markov chain that describes the algorithm's behaviour converges to a form in which all of the probability is focussed on the set of globally optimal solutions (conditional on the algorithm being convergent; otherwise, It will converge on a local optimum that might or might not be optimal.).

Typically, SA begins with a high temperature and an initial condition. Consider the state of the system at energy E. According to the analogy of thermodynamic systems, the function to be reduced is energy E. The energy level is Ei at state i. A random state j is formed by minor perturbations at a constant temperature T. Consider Ej to be the energy level in state j.

If $E_j \leq E_i$: State j will be approved immediately.

In other words, in the case of a minimization problem, the new solution is acceptable if the value of the objective function attained by this solution is less than the value attained by the previous solution.

If $E_j > E_i$: The Boltzmann distribution factor will be used to determine the probability that state j is accepted.

Boltzmann distribution factor $e^{-\frac{E_j - E_i}{k_B T}}$
Where, kB= Boltzmann constant, T= Temperature

The system reaches a steady state of thermal equilibrium at T. Assuming equilibrium has been reached, T can be lowered. This is done several times, or until the end condition is reached. T, the temperature, is the algorithm's control parameter, so its definition is crucial.

Important factors to take into account in this algorithm are the starting temperature, the iterations to be carried out at each respective temperature, and the rate of cooling. The optimal solution corresponds to the ground state of the system, while the other solutions correspond to other states.

Table 1: explains the connection between the simulated annealing terms and their physical annealing equivalents.

Table 1. Relationship between simulated annealing and physical annealing

Simulated Annealing	Physical Annealing
Objective function	Energy
Feasible Solutions	System States
Neighbouring Solutions	Change of State
Optimal Solution	Frozen State
Control parameter	Temperature

Figure 1 shows a process flow diagram for simulated annealing.

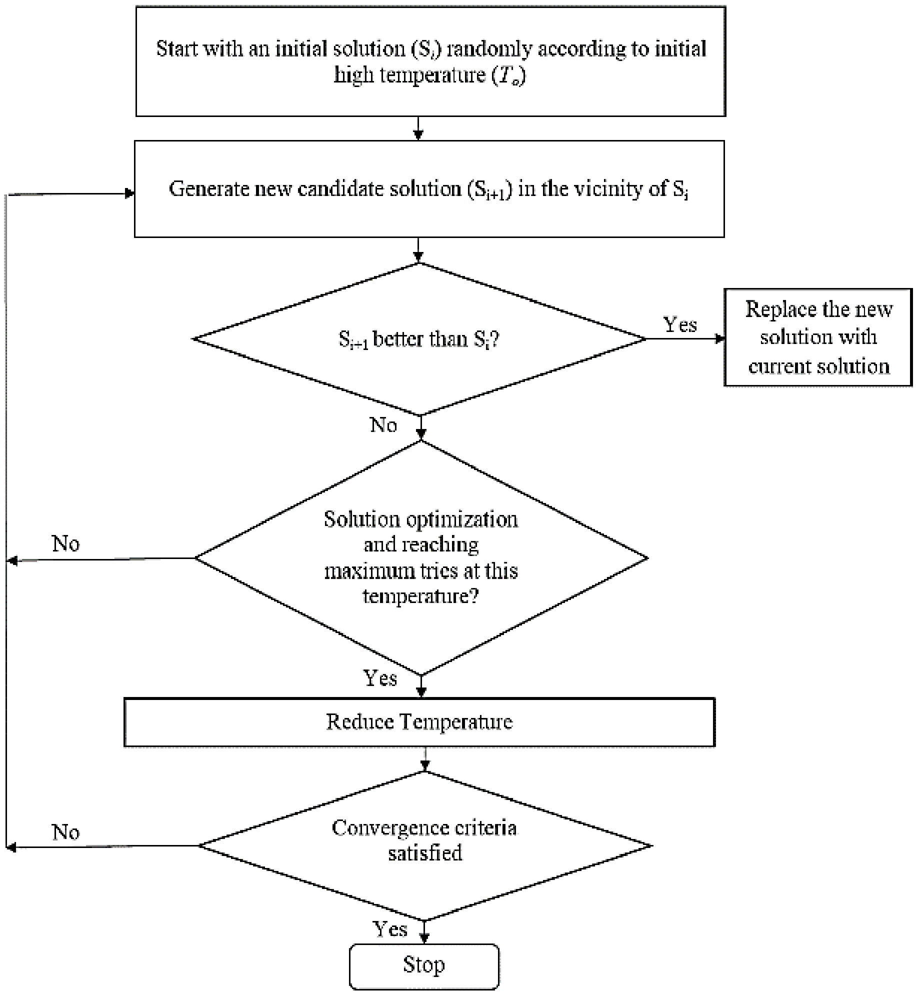

Figure 1: Flow chart of a simulated annealing algorithm

III. APPLICATIONS OF SIMULATED ANNEALING

Large-scale end-of-life products such as refrigerators and cars, are becoming more prevalent, which has a non-positive environmental repercussions and results in the squandering of non-renewable resources. The high-efficiency two-sided disassembly line is crucial in the recycling of such products. In order to simultaneously optimize the weighted length, workload smoothness index, and overall energy consumption, Liang et al. [3] developed the two-sided disassembly line balance problem with complex execution restrictions. In order to increase the variety of Pareto-optimal solutions, a dual-individual SA technique with multi-objective was created. This approach used two alternative neighbour structure strategies and a two-point mapping information exchange mechanism. Following the design of six benchmark testing problems of varying sizes, the method was assessed using the single-objective, multi-objective, and NSGA-II simulation annealing techniques. The findings showed that the suggested model and algorithm may satisfy the challenging task assignment execution limitations, significantly raise the smoothness index, and lower energy usage.

It has become crucial to have an optimum facility layout because the major goal of Industry 4.0 is to decrease the time and cost required to make the items. In other words, a well-organized layout of the equipment and workstations minimises the transportation of materials. Sulaiman et al. [4] investigated to locate the best placement of the available machines and workstations in the floor shop while also satisfying the limitations by means of the SA algorithm. As a result, the items and materials will move through the workplace in the quickest possible manner and over the shortest distance. A secondary objective of the project was to design a green, user-friendly layout with a low emission rate.

The two most crucial concerns in manufacturing are process modelling and machining parameter optimization. It is crucial to choose the right process parameters while drilling glass fibre reinforced polymer composites. Nayak et al. [5] worked on parametric optimization using simulated annealing. Three input parameters are taken into consideration for drilling at four different levels: cutting speed, feed rate, and drill size. It is possible to state that the proposed method offers support to tool engineers. It is worthy in particular for the purpose of optimizing a variety of performance indicators prior to drilling for a variety of cutting conditions and bit sizes.

Equipment and machine maintenance is a crucial aspect of the industrial function, and an efficient maintenance strategy can considerably contribute by providing value to production activities. For a multicomponent system, a selective maintenance decision model to decide whether to repair, replace, or do no action was presented by Tambe [6]. The objective functions in this approach were the overall cost of the maintenance choice. The decision variables were optimised using the simulated annealing process. The model generates maintenance actions for each component, including repair, replacement, and doing nothing. For maintenance managers to choose maintenance actions for specific machine components, the proposed research is helpful.

The primary barrier to floating wind turbine (FWT) development is stability and safety. For the purpose of enhancing the stability of Spar-type FWT, an active vibration control system was proposed by Mu et al. [7]. SA algorithm was used to create the weight of the linear quadratic regulator controller in order to remove subjectivity from parameter selection. Results demonstrate that the approach described here can significantly increase the stability and security of Spar-type FWTs.

For a closed Brayton cycle system using supercritical carbon dioxide (S-CO2), centrifugal flow compressor design and performance prediction models have been created by Tang et al. [8]. Additionally, the effects of blade number and inlet and outlet angles on compressor performance are examined. According to the results, the current compressor's outlet blade angle should be increased while the number of blades and inlet angle should be decreased to increase the compressor's efficiency under design conditions. The simulated annealing approach was used to enhance the performance of the current compressor under normal conditions. When the structural parameters were changed by no more than 20%, its evaluated overall isentropic efficiency increased from 82.26% to 87.72%.

Huang et al. [9] proposed how to determine the mechanical properties of bulk material using the loading and unloading curves of an instrumented indentation test (IIT). Using a simulated annealing swarm particle optimization and iterative finite element modelling, they were able to extract mechanical parameters from IIT data, such as the strain-hardening exponent (n) and strain-hardening rate (K). A systematic investigation was conducted to examine the singularity of the observed traits. The results demonstrated that the mechanical properties determined in this manner are distinct and accurate. The greatest errors of K and n caused by macro indentation testing were determined to be 8.2% and 6.3%, respectively. The mechanical properties discovered from ten loading-unloading curves were compared to those that are derived from a single loading-unloading curve. They discovered that 10 loading-unloading cycles of an indentation test produce more accurate mechanical characteristics.

Rapid developments in additive manufacturing technologies have created new opportunities and obstacles. One of the possible benefits of additive manufacturing is the ability to create systems with lower volumes/weights. The study by Cao et al. [10] focused on a form of configuration optimization problems in which the envelope volume in space occupied by a number of components must be decreased in addition to other goals. Two variants of a recently developed better multi-objective simulated annealing method, known as MOSA/R, were introduced to tackle this difficult problem after the mathematical formulation of a representative problem of configuration optimization with several hard constraints was presented. Experimental results show that the novel technique greatly outperforms the state-of-the-art on both benchmarks with limitations and the constrained configuration optimization issue.

Heat transport to the superheaters has a significant impact on the overall energy efficiency of recovery boiler power plants. The optimization of the a priori geometry using reliable numerical methods presents a significant problem in the design of such extremely large-scale systems. Maakala et al. [11] endeavored to demonstrate a computational optimization framework and adjust the design of the superheater zone in order to improve heat transfer. A surrogate-based analysis and optimization (SBAO) approach is used to construct the CFD-optimization framework; this method includes a simulated annealing optimization algorithm, a local polynomial regression surrogate model, and a Reynolds-averaged Navier-Stokes (RANS) CFD model. The results showed that the heat transfer rate was improved by 5% and the flow field was more uniform.

In order to enhance cooling while reducing electrical consumption, Navarro et al. [12] worked to identify the ideal shape, gains, and duration of an electric pulse applied to a Peltier cell, as well as the length of the thermoelectric. Simulated annealing is used for the highly non-linear optimization. The results of an initial parametric study, in which the relevance of several parameters were assessed. The preliminary investigation provided insight into how different shapes influence the development of chilly face temperature.

Shah et al. [13] presented a novel fitting method that enables an effective part-by-part reconstruction or update of editable CAD models corresponding to the point cloud of a digital mechanical parts' assembly. Utilizing parameterized CAD models whose dimensional parameters are tailored to fit the collected point cloud was the plan. The optimization kernel uses a simulated annealing approach to determine the optimal parameter values for minimizing the discrepancies between the point cloud and the to-be-fitted CAD models. Single and multiple components can be assembled sequentially or concurrently. Results range from the global fitting of a single component to the update of a comprehensive Digital Mock-Up with assembly limitations. The proposed method is able to assist in preserving the coherence between a product/system and its digital twin.

Correia et al. [14] worked on optimising the design of metal–ceramic plates subjected to thermomechanical loads by varying the thickness of functionally graded material (FGM) plates. FGM plates were optimised for minimum mass and minimum material cost using constrained optimization. In order to achieve a specific structural behaviour while optimising material costs and/or plate mass, the design process for FGM plate structures necessitates a careful selection of metal and ceramic materials and a precise definition of the volume fractions of the components along the thickness direction. Using the simulated annealing (SA) algorithm, optimization problems are solved without calculating the derivatives of the objective or constraint functions. As design variables, the p-index and the thickness of the FGM plate are used to study and validate cases of constrained single objective optimization. For the objectives of benchmarking and to demonstrate that the SA algorithm is suitable for handling these optimization issues, new optimization examples are presented that involve additionally the metal and ceramic materials as design variables.

Mesic et al. [15] presented the development process of the knowledge-based engineering (KBE) system for the structural size optimization of an external fixation device. The system employs methods for generative modelling, finite element model (FEM) analysis, and size optimization. Integration of a global algorithm based on the simulated annealing (SA) method and a local algorithm based on the conjugate gradient (CG) approach produces an iterative hybrid optimization process. Minimizing the design volume is the cost function for size optimization. Constraints are provided in the form of clinical interfragmentary displacement constraints at the fracture site and maximum permitted stresses for the external fixation device's material. As design parameters of the external fixation device, optimization variables are chosen. In comparison to the first model, the modified external fixation device has a smaller mass, improved stress distribution, and less interfragmentary displacement.

The three most important decisions in designing manufacturing cells are cell formation, facility layout, and scheduling. A mathematical model was established by Forghani et al. [16] to establish the machine cells, the arrangement of machines and workstations on the shop floor, the processing route of components, and the production sequence of activities on the machines. This computational model sought to reduce material handling expenses and production cycles as much as possible. It was proposed to use linear programming in conjunction with a Population-based Simulated Annealing (PSA) to efficiently solve the problem.

Using an artificial neural network, research has been done by Zhu [17]to investigate how to improve the performance of high-alloy, high-strength and high-toughness steel. Combining the simulated annealing algorithm with the backpropagation algorithm makes it possible to improve the learning efficiency of the network, as well as the selection of network structure, assessment of momentum coefficient, and learning rate. This was accomplished by making these aspects of the algorithm more reasonable. The findings can be applied to the design of high strength and high toughness steel's composition as well as the optimization of the steel's heat treatment process.

Among the many steps that comprise Computer Aided Process Planning, cutting conditions optimization is an essential one. Using a suggested Hybrid Genetic Simulated Annealing Algorithm, Jabri et al. [18] tackled the problem of optimising multipass turning operations. In order to prevent the genetic algorithm (GA) from becoming trapped inside the confines of a single local optimal solution, the simulated annealing based local search was effectively incorporated into a GA search mechanism. In this particular body of work, the cost per unit of production was taken into consideration as an objective function to be minimised in accordance with a variety of practical and operational restrictions. The effectiveness of the suggested method was presented when compared to other algorithms.

Laplume et al. [19] explained how the simulated annealing process could be used to solve a structural issue by determining the least weight of a circular plate that could support a given limit load. The plates under consideration were segmented into uniform ring-shaped sections. The thickness and size of each ring are design considerations due to the varying nature of the rings' boundaries. Each ring's thickness is constrained within a lower and higher bound, while the ring's breadth is constrained within a lower bound. It may be concluded from the results that the algorithm is both reliable and efficient.

As a means of speeding up the simulated annealing process, Cruz-Chávez et al. [20] presented a partial scheduling mechanism and a cooling schedule mechanism that are functions of the standard deviation. The flexible job shop scheduling challenge can be resolved more quickly and effectively as a result. Results showed that simulated annealing with the proposed mechanism converges to good solutions more quickly than simulated annealing without the proposed mechanism for benchmark instances of various sizes.

Thangadurai [21] proposed a solution to the balance issue consisting of a U-shaped assembly line that is created by a Simulated Annealing Algorithm. When compared to other lines, the simulated annealing algorithm's results for the shared U-shaped assembly line have shown significantly higher levels of productivity and efficiency.

Because of the significant initial investment, tooling expense, operating cost, and maintenance cost that are associated with sophisticated machining processes, it is imperative that the optimal selection of process parameters be made. Rao et al. [22]presented the findings of their work to optimise the process parameters of advanced machining processes of the mechanical type by making use of a simulated annealing technique. The findings that were acquired are then compared with the results that were produced employing a genetic algorithm. In the work, it has been marked that the simulated annealing has done better than the genetic algorithm.

The process of maximising the overall profit of a coal-fired thermal power plant is a very difficult and involved job. Using modelling, simulation, and optimization tools, in the work presented by Kumar [23], the primary emphasis was placed on determining the level of redundancy present in the coal-fired power plant's many different components and subsystems.

Thermoelectric cooling is an effective cooling technique that is particularly useful in harsh environments such as those found in gas drilling and thermal energy operations. Limitations in the thermoelectric cooling instrument's design, such as a relatively low energy conversion efficiency and the capacity to disperse only a limited quantity of heat flux, have the potential to cause significant harm to the instrument's lifetime and performance. Khanh [24] suggested an innovative strategy for maximising the cooling rate by optimising the dimensions of the TEC through the use of simulated annealing. They came up with a more effective geometric design for a single-stage thermoelectric cooler, that maximized the cooling rate.

Under dynamic conditions, it is necessary to conduct additional research on the utilisation of springs made of rubber-based materials within the clutch system. It has been proposed by Genç et al. [25] that a novel method be used for the application of damper springs made of elastomer in the clutch system of automobiles. A simulation of driving the vehicle with the clutch engaged was performed using a torsional fatigue test. Based on the results of the testing, a desired level of clutch stiffness was determined; next, a simulated annealing algorithm was written in Python and implemented with the help of targeted design constraints derived from the response surface technique.

IV. CONCLUSION

In the field of computational intelligence, metaheuristic techniques have proven to be an attractive tool for solving complex optimization problems. In this paper, the applications of simulated annealing, a metaheuristic for global optimization was reviewed. The ease with which SA can be implemented is arguably its greatest strength. Constraints can be easily integrated into simulated annealing algorithms by simply adding the corresponding constraint values to the values evaluated at each step. One of simulated annealing's biggest flaws is that it can get stuck at a local minimum. However, with the right annealing plan and initial conditions, this can be avoided to some extent. This work provides an overview of the many practical uses of simulated annealing in the field of mechanical engineering, from heat transfer issues to material science and manufacturing.

REFERENCES

[1] S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi, “Optimization by Simulated Annealing,” Science (1979), vol. 220, no. 4598, pp. 671–680, May 1983, doi: 10.1126/SCIENCE.220.4598.671.

[2] X.-S. Yang, Engineering Optimization: An Introduction with Metaheuristic Applications | Wiley. John Wiley & Sons, New Jersey.

[3] J. Liang et al., “Minimizing energy consumption in multi-objective two-sided disassembly line balancing problem with complex execution constraints using dual-individual simulated annealing algorithm,” J Clean Prod, vol. 284, p. 125418, Feb. 2021, doi: 10.1016/J.JCLEPRO.2020.125418.

[4] S. S. Sulaiman, P. Leela Jancy, A. Muthiah, V. Janakiraman, and S. J. P. Gnanaraj, “An evolutionary optimal green layout design for a production facility by simulated annealing algorithm,” Mater Today Proc, vol. 47, pp. 4423–4430, Jan. 2021, doi: 10.1016/J.MATPR.2021.05.256.

[5] B. B. Nayak, S. Kundu, M. Kumar, V. Kumar, R. Kumar, and K. P. Shivam, “Parametric optimization in drilling of GFRP composites using desirability function integrated simulated annealing approach,” Mater Today Proc, vol. 44, pp. 1983–1987, Jan. 2021, doi: 10.1016/J.MATPR.2020.12.116.

[6] P. P. Tambe, “Selective Maintenance Optimization of a Multi-component System based on Simulated Annealing Algorithm,” Procedia Comput Sci, vol. 200, pp. 1412–1421, Jan. 2022, doi: 10.1016/J.PROCS.2022.01.342.

[7] A. Mu, Z. Huang, A. Liu, J. Wang, B. Yang, and Y. Qian, “Optimal model reference adaptive control of spar-type floating wind turbine based on simulated annealing algorithm,” Ocean Engineering, vol. 255, p. 111474, Jul. 2022, doi: 10.1016/J.OCEANENG.2022.111474.

[8] S. Tang, M. Peng, G. Xia, G. Wang, and C. Zhou, “Optimization design for supercritical carbon dioxide compressor based on simulated annealing algorithm,” Ann Nucl Energy, vol. 140, p. 107107, Jun. 2020, doi: 10.1016/J.ANUCENE.2019.107107.

[9] L. Y. Huang, K. S. Guan, T. Xu, J. M. Zhang, and Q. Q. Wang, “Investigation of the mechanical properties of steel using instrumented indentation test with simulated annealing particle swarm optimization,” Theoretical and Applied Fracture Mechanics, vol. 102, pp. 116–121, Aug. 2019, doi: 10.1016/J.TAFMEC.2019.04.009.

[10] P. Cao, Z. Fan, R. X. Gao, and J. Tang, “Harnessing multi-objective simulated annealing toward configuration optimization within compact space for additive manufacturing,” Robot Comput Integr Manuf, vol. 57, pp. 29–45, Jun. 2019, doi: 10.1016/J.RCIM.2018.10.009.

[11] V. Maakala, M. Järvinen, and V. Vuorinen, “Optimizing the heat transfer performance of the recovery boiler superheaters using simulated annealing, surrogate modeling, and computational fluid dynamics,” Energy, vol. 160, pp. 361–377, Oct. 2018, doi: 10.1016/J.ENERGY.2018.07.002.

[12] P. Moreno-Navarro, J. L. Pérez-Aparicio, and J. J. Gómez-Hernández, “Optimization of pulsed thermoelectric materials using simulated annealing and non-linear finite elements,” Appl Therm Eng, vol. 120, pp. 603–613, Jun. 2017, doi: 10.1016/J.APPLTHERMALENG.2017.04.036.

[13] G. A. Shah, A. Polette, J. P. Pernot, F. Giannini, and M. Monti, “Simulated annealing-based fitting of CAD models to point clouds of mechanical parts’ assemblies,” Engineering with Computers 2020 37:4, vol. 37, no. 4, pp. 2891–2909, Feb. 2020, doi: 10.1007/S00366-020-00970-8.

[14] V. F. Correia, J. S. Moita, F. Moleiro, and C. M. M. Soares, “Optimization of Metal–Ceramic Functionally Graded Plates Using the Simulated Annealing Algorithm,” Applied Sciences 2021, Vol. 11, Page 729, vol. 11, no. 2, p. 729, Jan. 2021, doi: 10.3390/APP11020729.

[15] E. Mešić, N. Pervan, A. J. Muminović, A. Muminović, and M. Čolić, “Development of Knowledge-Based Engineering System for Structural Size Optimization of External Fixation Device,” Applied Sciences 2021, Vol. 11, Page 10775, vol. 11, no. 22, p. 10775, Nov. 2021, doi: 10.3390/APP112210775.

[16] K. Forghani, S. M. T. Fatemi Ghomi, and R. Kia, “Concurrent scheduling and layout of virtual manufacturing cells considering assembly aspects,” https://doi.org/10.1177/0954405420980685, vol. 235, no. 6–7, pp. 1036–1049, Dec. 2020, doi: 10.1177/0954405420980685.

[17] L. Zhu, “Optimization Simulated Annealing Algorithm for High Strength and Toughness Metal,” pp. 720–724, 2021, doi: 10.1007/978-3-030-79200-8_107.

[18] A. Jabri, A. el Barkany, and A. el Khalfi, “Multipass Turning Operation Process Optimization Using Hybrid Genetic Simulated Annealing Algorithm,” Modelling and Simulation

in Engineering, vol. 2017, Jun. 2017, doi: 10.1155/2017/1940635.
[19] D. Laplume and D. Lamblin, "Simulated annealing applied to the optimal plastic design of circular steel plates," Int J Numer Methods Eng, vol. 73, no. 8, pp. 1047–1060, Feb. 2008, doi: 10.1002/NME.2094.
[20] M. A. Cruz-Chávez, M. G. Martínez-Rangel, and M. H. Cruz-Rosales, "Accelerated simulated annealing algorithm applied to the flexible job shop scheduling problem," International Transactions in Operational Research, vol. 24, no. 5, pp. 1119–1137, Sep. 2017, doi: 10.1111/ITOR.12195.
[21] v. Thangadurai, "Meta Heuristic Based Simulated Aneling Approach for Design of U-shaped Manufacturing Assembly Line Balancing," Journal of New Materials for Electrochemical Systems, 2018, Accessed: Dec. 02, 2022. [Online]. Available: https://www.iieta.org/journals/jnmes/paper/10.14447/jnmes.v21i3.a07
[22] R. V. Rao, P. J. Pawar, and J. P. Davim, "Optimisation of process parameters of mechanical type advanced machining processes using a simulated annealing algorithm," International Journal of Materials and Product Technology, vol. 37, no. 1–2, pp. 83–101, 2010, doi: 10.1504/IJMPT.2010.029461.
[23] R. Kumar, "Redundancy optimisation of a coal fired power plant using simulated annealing technique," International Journal of Intelligent Enterprise, vol. 4, no. 3, pp. 191–203, 2017, doi: 10.1504/IJIE.2017.087625.
[24] D. V. K. Khanh, P. M. Vasant, I. Elamvazuthi, and V. N. Dieu, "Geometric optimisation of thermo-electric coolers using simulated annealing," International Journal of Computational Science and Engineering, vol. 14, no. 3, pp. 279–289, 2017, doi: 10.1504/IJCSE.2017.084164.
[25] M. O. Genç, S. Konakçı, N. Kaya, S. Kartal, and A. K. Serbest, "Development of a novel testing procedure and optimisation of a rubber spring using constrained simulated annealing algorithm for automobile clutch system," International Journal of Vehicle Design, vol. 88, no. 1, pp. 33–55, 2022, doi: 10.1504/IJVD.2022.124869.