ISSN No:-2456-2165

Modeling and Optimization of Vapor Absorption Refrigeration Systems: A Computational Intelligence Overview

*[1]Kapil Jain; *[2]Basant Kumar Chourasia
[1,2]Department of Mechanical Engineering, Jabalpur Engineering College,
Jabalpur, (M.P.), India

Corresponding author:- *[1]Kapil Jain; *[2]Basant Kumar Chourasia

Abstract:- This literature review delves into the utilization of computational intelligence techniques, such as Simulated Annealing (SA), Differential Evolution (DE), Heat Transfer Search (HTS), Chemical Reaction Optimization (CRO), Multi-Objective GA (MOGA), and Nondominated Sorting Genetic Algorithm II (NSGA II), for modeling and optimizing vapor absorption refrigeration systems. The inherent complexity of modern refrigeration systems, characterized by their multi-modal, non-linear, and time-consuming optimization problems, necessitates the application of advanced computational tools. These techniques have demonstrated success in overcoming the challenges posed by the intricate nature of refrigeration system optimization. Through trend analysis, the primary focus of optimization is identified as the COP, followed by considerations for total cost, exergetic and energetic efficiency, energy consumption, and cooling capacity. Computational intelligence methods prove effective in addressing these objectives. This review critically evaluates the outcomes of employing such techniques, emphasizing both advancements and shortcomings in existing methodologies. As the demand for energy-efficient refrigeration solutions grows, this comprehensive literature review contributes valuable insights into state-of-the-art computational intelligence approaches for optimizing vapor absorption refrigeration systems. The findings serve as a foundation for future research directions, underscoring the significance of intelligent optimization strategies in addressing the multifaceted challenges within the field of refrigeration technology.

Keywords:- *Simulated Annealing (SA), Differential Evolution (DE), Heat Transfer Search (HTS), Chemical Reaction Optimization (CRO), Multi-Objective GA (MOGA), Nondominated Sorting Genetic Algorithm II (NSGA II), COP, Optimization.*

I. INTRODUCTION

The refrigeration sector plays a pivotal role in global energy consumption and environmental impact, with profound implications for industries worldwide. As societies become increasingly reliant on refrigeration for various applications, it is crucial to examine the broader consequences of this dependence. Refrigeration systems, essential for preserving and maintaining a wide range of products, contribute significantly to the escalating demand for electricity on a global scale. This surge in energy consumption is intricately linked to environmental concerns, as the refrigeration industry is a major contributor to both greenhouse gas emissions and ozone depletion potential.

In the context of escalating environmental challenges, the 2015 Paris Conference Agreement emerged as a milestone in addressing the crisis. The agreement brought nations together to collectively combat climate change and limit global warming to well below 2 degrees Celsius. Amidst these concerns, optimizing refrigeration systems becomes imperative to reduce their adverse environmental impact. Computational intelligence approaches, including SA, DE, HTS, CRO, MOGA, and NSGA II, have emerged as powerful tools for enhancing the efficiency and sustainability of refrigeration systems.

This paper aims to explore the intersection of refrigeration systems, their impact on worldwide electricity consumption, and their environmental footprint. By delving into the intricacies of computational intelligence techniques, we seek to highlight the potential of these approaches in optimizing refrigeration systems, contributing to the global effort in mitigating environmental crises outlined in the Paris Conference Agreement.

II. VAPOR ABSORPTION REFRIGERATION SYSTEM

The vapor absorption system is comprised of a binary mixture involving refrigerant and absorber constituents. Typically, the absorption process is characterized by an exothermic nature, wherein the absorber facilitates the absorption of liquid refrigerant through vaporization, thereby inducing a cooling effect. The VARS is conventionally constituted by key components including an absorber, condenser, evaporator, expansion valve, generator, pump, and rectifier. The operational sequence initiates with the provision of external heat to the generator, resulting in an elevation of temperature and pressure. Consequently, the strong solution liquid-state refrigerant undergoes a phase transition to the vapor state. The vaporized refrigerant proceeds to the condenser, where it releases heat to the surrounding atmosphere and undergoes a transformation into the liquid phase.

Subsequently, the refrigerant experiences further expansion in the expansion valve, leading to a reduction in both temperature and pressure. The low-temperature and low-pressure refrigerant entering the evaporator absorbs heat from the enclosed space, thereby generating a cooling effect. The absorber is instrumental in converting the refrigerant, having absorbed latent heat of evaporation, into a vapor state. This vapor then combines with a weak solution within the absorber before being pumped into the generator, thus completing the cycle.

The inclusion of a rectifier subsequent to the generator serves the primary purpose of thoroughly eliminating any residual traces of water vapor present in the refrigerant before its entry into the condenser.

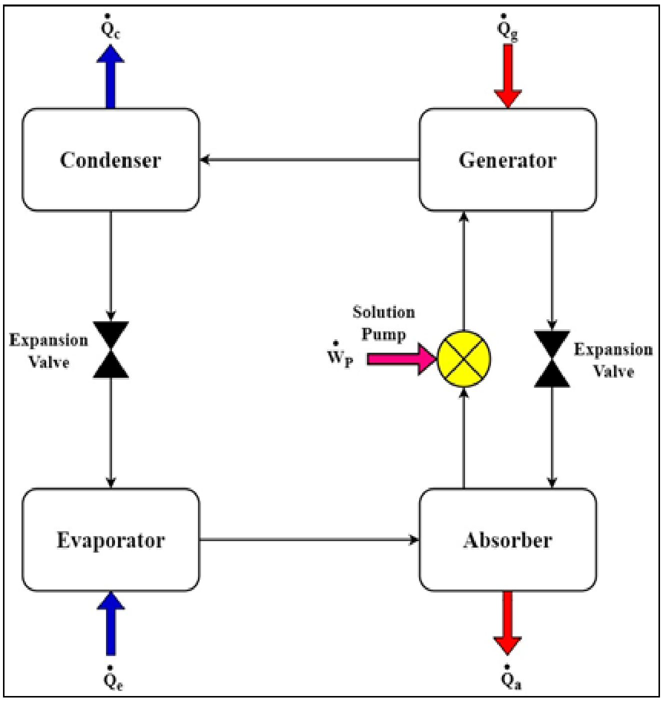

Fig 1 Schematic of Vapor Absorption Refrigeration System

The mathematical derivation of the Coefficient of Performance for absorption refrigeration can be expressed using the provided mathematical expression:

$$\mathbf{COP} = \frac{Q_E}{Q_G+W_p} \tag{1}$$

Where COP = Coefficient of Performance.

Q_E = Cooling Capacity obtained at the evaporator.

Q_G = Heat supplied to the Generator.

W_P = Work input to the pump.

➤ *The Considerations for the Refrigerant in the Absorption Refrigeration System Encompass the Following Assumptions:*

- The refrigerant is required to exhibit chemical stability, non-toxicity, and non-volatility.
- The refrigerant must possess a substantial heat of vaporization.
- The mixture of refrigerant and absorber should demonstrate miscibility within the designated operating temperature range.
- A considerable disparity in the boiling point temperatures of the refrigerant and absorber is preferred.
- Transport properties influencing heat and mass transfer, including thermal conductivity, viscosity, and diffusion coefficient, should be conducive.
- The refrigerants should manifest non-corrosive characteristics, environmental friendliness, abundance, and affordability.

III. COMPUTATIONAL INTELLIGENCE METHODS FOR ENHANCED MODELING AND OPTIMIZATION OF VAPOR ABSORPTION REFRIGERATION SYSTEMS

Computational Intelligence (CI) techniques encompass a diverse set of computational methodologies inspired by natural intelligence and adaptive systems. In the context of modeling and optimization of VARS, CI methods play a crucial role in enhancing efficiency, reliability, and performance.

Vapor absorption refrigeration systems are complex and dynamic, involving numerous parameters and nonlinear relationships. Traditional analytical methods often struggle to capture the intricacies of these systems. This is where CI techniques shine, as they are designed to handle complex and uncertain systems, making them particularly well-suited for modeling and optimizing VARS.

➤ *Simulated Annealing (SA)*

Simulated Annealing (SA) is a stochastic optimization algorithm inspired by the annealing process in metallurgy, where a material is heated and then slowly cooled to remove defects and optimize its internal structure. Similarly, SA is used to find the global optimum of a function by iteratively exploring the solution space and accepting probabilistically worse solutions to escape local minima. In optimizing VARS using Simulated Annealing, the process involves several key steps. Firstly, an objective function is defined to assess system performance, considering factors like the COP, energy consumption, and exergetic efficiency. Next, a solution is represented by specifying values for parameters influencing the system, such as temperatures and pressures. The optimization process begins with an initial randomly generated solution and a set temperature, controlling the likelihood of accepting worse solutions. Iterations follow, where the solution is perturbed, exploring neighboring solutions. A cooling schedule gradually reduces the temperature, balancing exploration and exploitation. The Metropolis acceptance criterion is applied to determine

ISSN No:-2456-2165

whether to accept a new solution, considering its impact on the objective function. A termination condition, like reaching a specific temperature or maximum iterations, ensures convergence. The final output represents an optimized configuration for the VARS based on the defined objective function.

SA provides a robust and effective approach for tackling the complex, nonlinear, and multi-modal optimization challenges associated with VARS. Its ability to explore the solution space globally makes it a valuable tool for finding near-optimal solutions in a computationally efficient manner.

Chen, Luo, and Yuan (2023) tackled the complex but promising challenge. A stochastic optimization technique for the synthesis of CRS is explored in the present study. Based on the designed superstructure for the CRS, a MINLP paradigm has been developed. The number of pressure/temperature levels for each sub-refrigeration system was repeatedly determined using an optimization framework that included a simulated annealing approach. In addition, the continuous variables in the system were optimized using a PSO approach. of designing a CRS while also taking heat integration between refrigerant and process streams into account. The efficacy of the proposed methodology was demonstrated through a case study involving the optimization of a CRS in an ethylene plant, resulting in a substantial 21.89% reduction in the total annual cost. This outcome underscores the potential for significant cost savings and carbon emission reduction achievable through the proposed stochastic optimization approach.

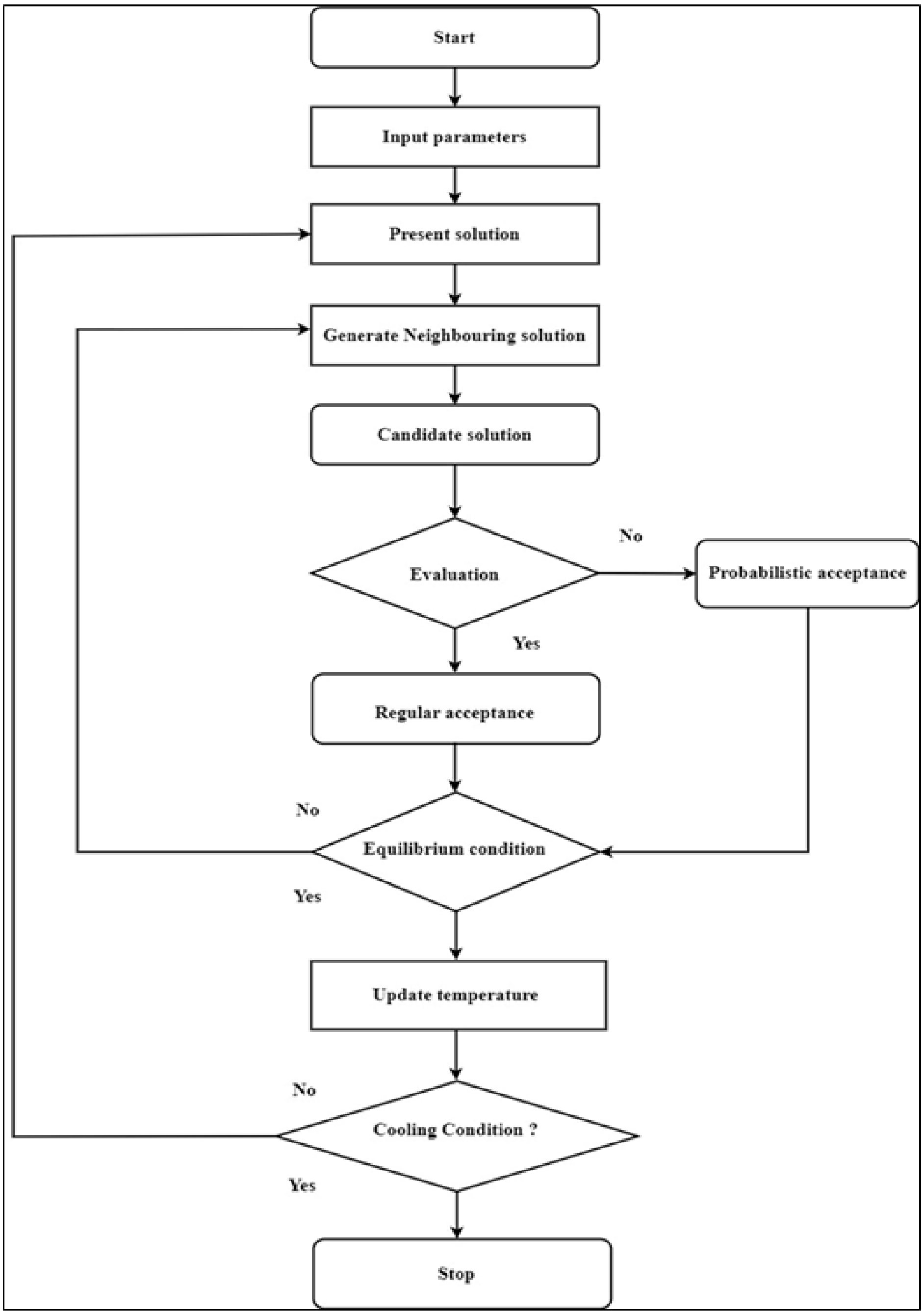

Fig 2 Schematic of the Simulated Annealing Technique

Mahadzir and Ahmed (2021) investigate the significance of multistage refrigeration systems in industrial applications, employing evolutionary computation techniques (PSO, GA, and SA) to optimize a two-stage vapor compression refrigeration system. The study aims to minimize energy consumption and maximize the system's COP. Design parameters are validated against literature data, showing acceptable results. Optimal solutions yield a 30.8% reduction in energy consumption and a nearly 77% increase in COP compared to the design basis. Enhanced optimization procedures prevent early convergence, and PSO proves to be more efficient in terms of computational effort, time, and implementation compared to GA and SA.

Maakala, Järvinen, and Vuorinen (2018) focus on optimizing the heat transfer to superheaters in recovery boiler power plants. They introduce a numerical optimization framework addressing a key challenge in large-scale applications. The study employs a surrogate-based method, combining simulated annealing, local polynomial regression, and computational fluid dynamics. Key contributions include introducing the optimization framework, quantifying the geometry-heat transfer connection, and identifying optimal designs for existing recovery boilers. Results show a 5% increase in heat transfer rate with improved flow field uniformity, emphasizing the importance of minimizing separation vortices through geometric design. This study showcases the potential of optimization methods in large-scale energy production applications for the first time.

Chang et al. (2017) employed SA technique to effectively address the Lagrangian method's adaptability issues in handling non-convex functions within power consumption models or kW–PLR curves for the OCL problem. Choosing the chilled water supply temperature as the decoupled system variable, the study demonstrated that SA provided highly accurate results swiftly, making it suitable for efficient air conditioning system operation. In contexts where traditional centralized air conditioning systems lack substantial freezing capacity, have few units, and exhibit simpler operational methods with limited OCL consideration, SA proved effective in overcoming the Lagrangian method's limitations for optimal efficiency in the semiconductor industry.

➢ *Differential Evolution (DE)*

Differential Evolution (DE) is a population-based optimization algorithm particularly suitable for continuous, nonlinear, and multi-modal optimization problems.

In optimizing VARS using the DE technique, the process involves key steps. Firstly, the solution space is defined by specifying upper and lower bounds for parameters like temperatures, pressures, and concentrations. An initial population of potential solutions is generated within this space, with each solution representing a set of parameter values. The DE algorithm employs a mutation operation, selecting three individuals from the population to create trial solutions, introducing diversity. A crossover operation combines these trial solutions with the existing population, determining the incorporation of trial parameters based on a predefined probability. The selection mechanism compares trial solutions with the current population, retaining those with superior fitness values. Termination criteria, such as a maximum number of iterations or convergence, determine when the search concludes. The objective function, encompassing factors like the COP and energy consumption, is evaluated for each individual and trial solution. The final population is analyzed to extract optimized parameter values, representing an enhanced configuration for the vapor absorption refrigeration system based on the best-performing solutions.

DE is known for its robustness and ability to handle complex optimization problems. Its population-based nature and the interplay of mutation, crossover, and selection operations make it effective in exploring the solution space and converging to optimal solutions for VARS.

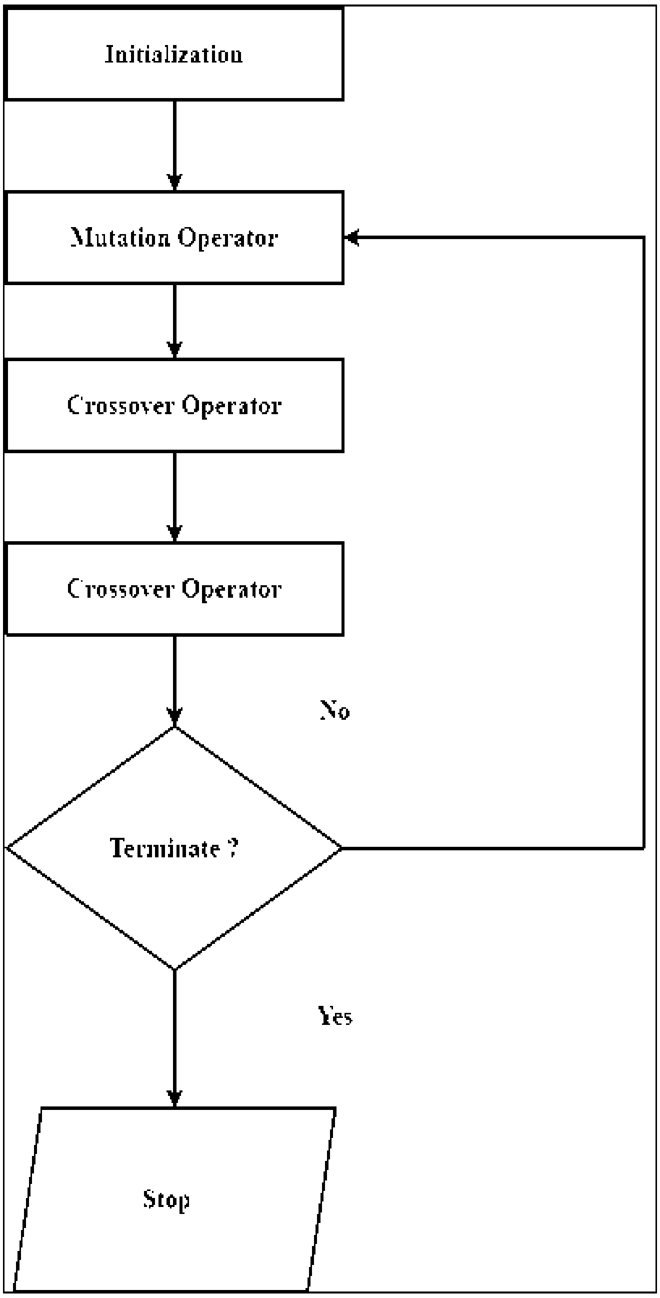

Fig 3 Schematic of the Differential Evolution Technique

Kong et al. (2021) introduce a global optimization approach using the SADE algorithm to minimize energy consumption in a VCRS while meeting indoor cooling requirements. The study establishes a simplified hybrid VCRS model based on thermodynamics, heat transfer theory, and parameter regression. A global optimization problem is formulated considering component interactions, indoor loads, and outdoor conditions. The SADE algorithm is employed, yielding optimal settings. Simulation results demonstrate the strategy's effectiveness, achieving an average 15.57% energy saving on typical testing days. Notably, significant energy savings are observed during morning and evening periods with partial indoor cooling loads. Comparisons with DE and classical PSO algorithms reveal SADE's efficiency in reducing calculation time and avoiding local minima, providing an effective methodology for reducing air conditioning system energy consumption.

Lin et al. (2019) employs a two-stage DE algorithm to optimize OCL problems in vapor compression refrigeration systems. The study includes two case studies involving six-chiller and four-chiller systems. Using the SADE algorithm, the proposed method achieves an average energy saving of 15.57% for the six-chiller system. Comparisons with DCSA, SA, and PSO show superior results for the two-stage DE algorithm. In the four-chiller system case study, the proposed method outperforms DCSA and other methods (genetic algorithm, PSO, DE, CSA under various cooling load conditions, demonstrating stability and effectiveness.

Wang, Cai, and Yin (2017) propose a globally optimized operation strategy to reduce energy consumption in an LDAC system driven by a chiller and electric heater. Energy and heat transfer models are developed for system components, and a SADE algorithm is employed for optimization. The strategy, tested on a fabricated facility, achieves an 18.5% energy saving compared to conventional methods, making it suitable for energy reduction in existing LDAC systems in buildings.

Lee et al., (2011) investigated optimal chiller loading for energy reduction using the DE algorithm, comparing its efficacy with the Lagrangian method, genetic algorithm, and particle swarm algorithm. Findings demonstrated DE's proficiency in identifying optimal solutions and outperforming other algorithms, particularly in addressing divergence issues at low demand. With specific parameters, DE exhibited competitive minimum energy consumptions with PSO in both cases, emphasizing its effectiveness in optimizing energy consumption, especially when the partial load ratio exceeded 60%. The study highlighted DE's consistent superiority in average energy consumption over PSO, contributing valuable insights into chiller loading optimization for enhanced energy efficiency.

- *Heat Transfer Search (HTS)*

Heat Transfer Search (HTS) is a nature-inspired optimization algorithm inspired by the heat transfer process in thermodynamics.

In the optimization of VARS using the HTS technique, the process involves several key steps. The heat transfer process is initialized by defining the initial heat distribution within the system. Each potential solution is represented as a heat source corresponding to system parameters such as temperatures, pressures, and concentrations. Simulating heat transfer operations between these sources, the algorithm mimics the movement of heat within the system, with the intensity of transfer influenced by the fitness of solutions. Fitter solutions contribute more significantly to the heat transfer process. The algorithm facilitates exploration and exploitation of the solution space, discovering potential configurations and refining the search around promising regions. Fitness evaluation assesses each solution's performance based on the objective function, considering parameters like the COP and energy consumption. Termination criteria, such as reaching a maximum number of iterations or achieving convergence, determine when the optimization process concludes. The final distribution of heat within the system is analyzed to extract optimized parameter values, representing an improved configuration for the VARS based on the solutions with the best fitness.

HTS leverages the principles of heat transfer to navigate the solution space, allowing for the exploration of potential configurations and the identification of optimal solutions for VARS. The algorithm's effectiveness lies in its ability to mimic the physical process of heat transfer to guide the search towards improved system performance.

Mansuriya et al. (2020) examine an exhaust heat-driven ejector refrigeration system, incorporating thermo-economic considerations. Using the HTS algorithm, the system is optimized for COP and total annual cost. Design variables include generator, evaporator, and condenser temperatures. The study employs a 2-D shock circle model with R245fa refrigerant and presents multi-objective optimization results through the Pareto frontier. Analysis of varying nozzle throat diameter and ecological function on thermo-economic objectives is discussed. Sensitivity analysis explores the influence of decision variables on objectives, and exergo-economic outcomes reveal the ejector and generator as major contributors to exergy destruction and total annual cost. At the optimal point, the system achieves a coefficient of performance of 0.3, a total annual cost of $25,903/year, and an optimized unit cost of $53.8/GJ with 10.5% exergy efficiency.

In the study conducted by Patel et al., (2019) the optimization and comparative analysis of a cascade refrigeration system employing the refrigerant pairs NH_3/CO_2 and C_3H_8/CO_2 were undertaken. The investigation focused on the thermo-economic optimization of a cascade refrigeration system utilizing CO_2 in the low-temperature circuit and NH_3 or C_3H_8 in the high-temperature circuit. The optimization process aimed at minimizing the total annual cost and exergy destruction of the system, considering four crucial operating parameters: evaporator temperature, condenser temperature, condensing temperature of the low-temperature circuit, and cascade temperature difference. To address the optimization problem, a HTS algorithm was employed, yielding Pareto-

ISSN No:-2456-2165

optimal points as the outcome. Comparative analysis of the refrigerant pairs (NH_3/CO_2 vs. C_3H_8/CO_2) based on the obtained results indicated that the C_3H_8/CO_2 pair exhibited a 5.33% lower cost and a 6.42% higher exergy destruction in comparison to the NH_3/CO_2 pair.

Pattanaik, Basu, and Dash (2019) propose the application of the heat transfer search (HTS) algorithm to address the intricate combined heat and power economic dispatch (CHPED) problem. This research incorporates considerations for the valve point effect, prohibited operating zones of traditional thermal generators, and transmission loss. The primary objective of solving the CHPED problem is to minimize the total fuel cost associated with electricity production and heat supply to meet load demand. HTS, a novel meta-heuristic optimization algorithm rooted in the principles of thermodynamics and heat transfer, is introduced. The efficacy of the HTS algorithm is validated through experimentation on four test systems. Comparative analysis with other evolutionary algorithms demonstrates that the suggested HTS algorithm outperforms in providing superior solutions.

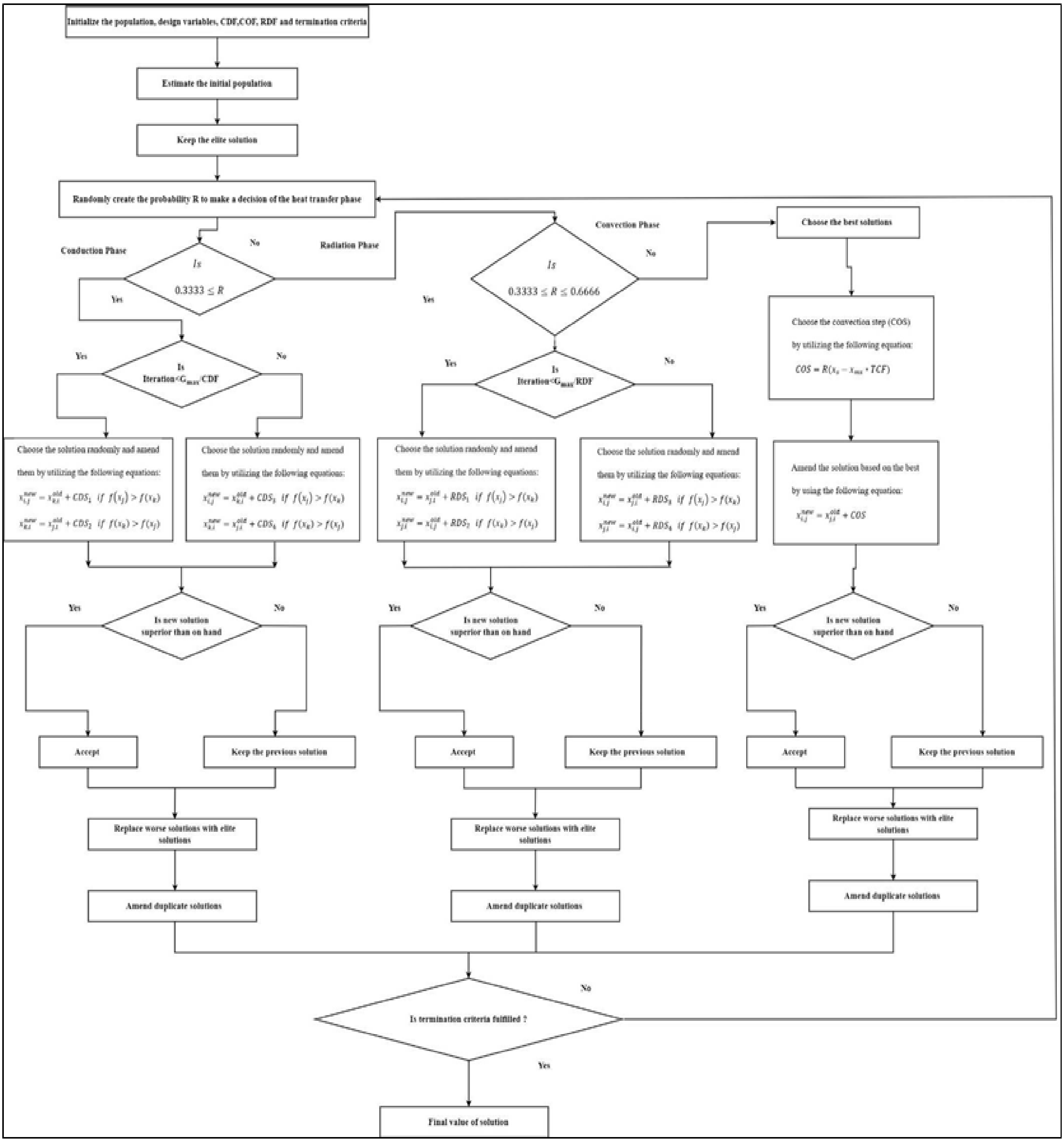

Fig 4 Schematic of the HTS Algorithm

Patel and Savsani (2015) introduce the Heat Transfer Search (HTS) algorithm, a novel global metaheuristic inspired by thermodynamics. Analogous to clusters of molecules, the algorithm represents a population engaged in a heat transfer process. Design variables correspond to molecule temperatures, and energy levels signify the objective function value. The search involves 'Conduction,' 'Convection,' and 'Radiation' phases, with factors controlling exploration and exploitation. HTS is assessed on 24 CEC 2006 benchmark problems, outperforming other algorithms in terms of solutions, success rate, and computational efficiency. Statistical analysis confirms its superiority in constrained optimization problems.

- *Chemical Reaction Optimization (CRO)*

Chemical reaction optimization is a nature inspired metaheuristic algorithm that draws inspiration from the principles of chemical reactions in order to optimize complex problems.

In the optimization of VARS using the CRO technique, the process involves distinctive steps. Each potential solution is represented as a chemical species, with system parameters like temperatures, pressures, and concentrations depicted as chemical reactants. Chemical reaction operators, including 'Chemical Reaction,' 'Molecule Diffusion,' and 'Chemical Attraction,' guide exploration and exploitation in the solution space. A population of molecules is initialized randomly, reflecting diverse potential solutions. The 'Chemical Reaction' operator combines information from different molecules to generate new solutions, influenced by their fitness.

'Molecule Diffusion' allows for exploration by modeling the diffusion of molecules, diversifying solutions. The 'Chemical Attraction' operator directs molecules towards promising solution regions, enhancing exploitation. Fitness evaluation assesses each molecule based on the objective function, including parameters like the COP and energy consumption. Termination criteria, such as reaching a maximum number of iterations or achieving convergence, determine when the optimization concludes. The final population of molecules is analyzed to extract optimized parameter values, representing an improved configuration for the vapor absorption refrigeration system based on the best-performing solutions.

CRO leverages the principles of chemical reactions to effectively explore and exploit the solution space. Its ability to simulate chemical reactions, molecule diffusion, and attraction operations contributes to its efficacy in optimizing VARS.

Hadidi (2017) proposed a novel optimization approach for electrically serial two-stage thermoelectric refrigeration systems using the CRO algorithm. A comprehensive computer code demonstrated the method's performance in two distinct test cases. The key performance parameters, cooling capacity, and COP were selected as objective functions. Comparative analyses with an analytical method and a genetic algorithm showed substantial enhancements in cooling capacity, approximately 16.7% and 12%, respectively. Implementation of the CRO method resulted in a notable 4.7% improvement in the coefficient of performance compared to the analytical method and an 8% enhancement relative to the genetic algorithm in the second part of case study 1. Comparisons with the genetic algorithm in case study 2 further highlighted improvements in the COP and cooling capacity across different conditions. The consistent enhancement in the coefficient of performance and cooling capacity affirmed the accuracy and superiority of the CRO method for optimal thermoelectric refrigeration system design.

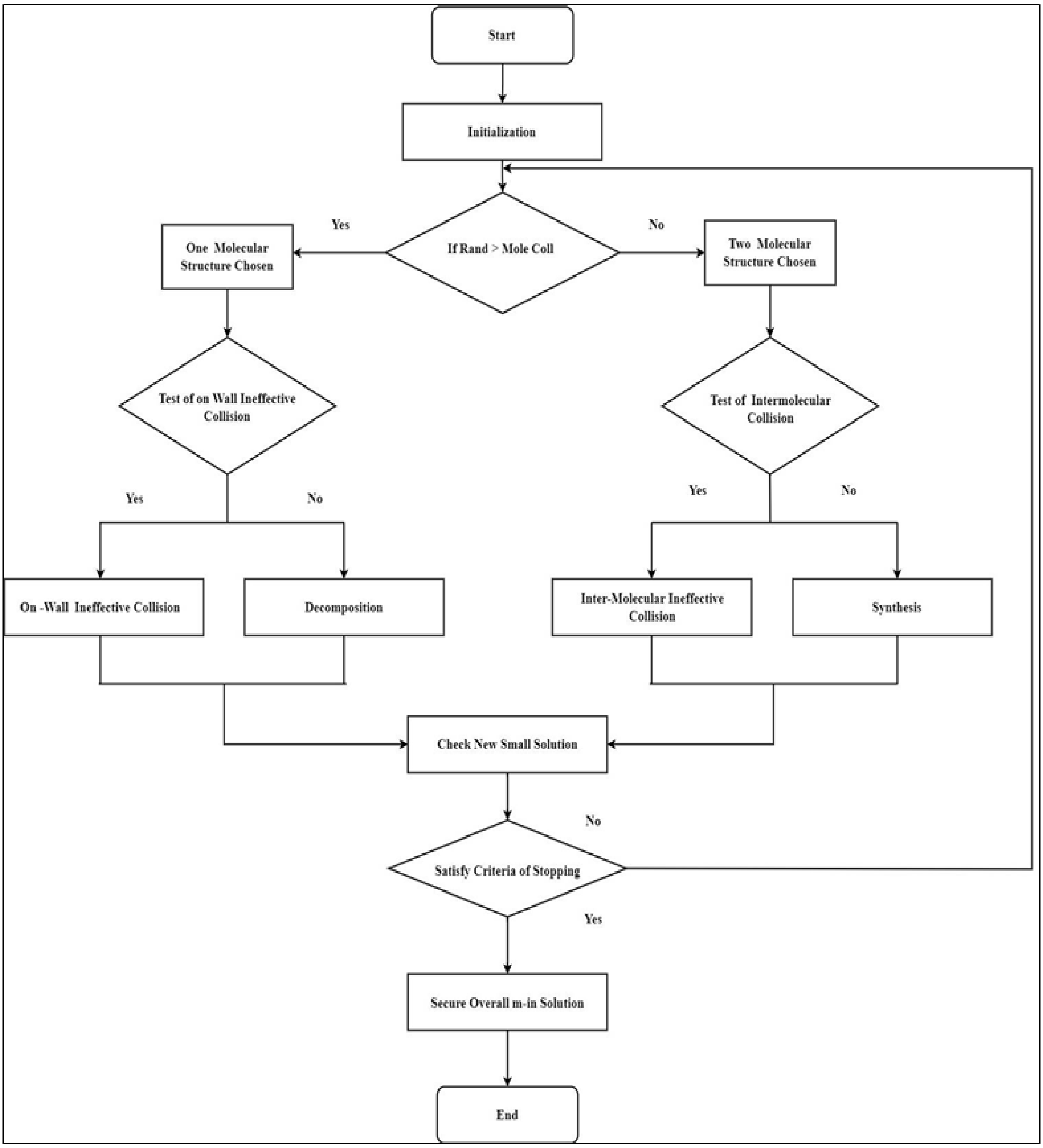

Fig 5 Schematic of the Chemical Reaction Optimization Technique

Hadidi (2017) proposes an efficient optimization approach, using the CRO algorithm, for the design of thermoelectric refrigeration systems. Overcoming the limitations of traditional trial-and-error methods, the study applies the CRO algorithm to two case studies. The objective functions, cooling capacity, and COP are optimized, resulting in a 4% improvement in cooling capacity in case study 1 and a 4.7% enhancement in COP in case study 2 compared to genetic algorithm results. The research emphasizes the effectiveness of the CRO algorithm in optimizing electrically separated two-stage thermoelectric refrigeration systems, suggesting the need for more efficient algorithms in system design. The study also explores the impact of varying thermal resistance on cooling capacity, providing valuable numerical insights. The demonstrated improvement validates CRO as an effective optimization method for thermoelectric refrigeration systems, with potential for future thermo-economic optimization studies.

To solve flexible job-shop scheduling problems with maintenance activity constraints, Li and Pan (2012) developed an effective DCRO technique. The algorithm simultaneously reduces three different goals: the overall machine workload, the critical machine burden, and the maximum completion time (makespan). The DCRO has four enhanced elementary reactions and a well-thought-out crossover function, using chemical molecules to represent solutions. By taking into account a decoding mechanism for maintenance activities, TS-based local search improves the exploitation process. Several nearby approaches further enhance the local search capabilities of the algorithm. Comparing the DCRO to top algorithms in the literature, experimental results on benchmark examples show the DCRO's extremely effective performance.

CRO, a metaheuristic inspired by chemical reactions that seeks to identify global minima in optimization problems, is introduced by Lam and Li (2010). CRO is a successful metaheuristic because of its proven ability to solve NP-hard problems such as QAP, RCPSP, and CAP. CRO complies with the NFL theory, and matches others in general, but performs best when customized for particular issue types. Understanding the drawbacks of the current metaheuristics, CRO offers an innovative and fruitful solution. The basic form of CRO is presented in this study, with potential for further improvements via hybridization with other techniques to tackle a wider variety of issues and find global optima for issues that were previously considered "unsolved".

➢ *Multi-Objective Genetic Algorithm (MOGA)*

Multi-Objective Genetic Algorithm (MOGA) is an optimization algorithm that aims to find solutions to problems with multiple conflicting objectives.

In the optimization of VARS using MOGA, the process involves several key steps. Multiple objective functions are defined to encompass various aspects of system performance, such as maximizing the COP and minimizing energy consumption while optimizing factors like exergetic efficiency and cooling capacity. Each potential solution is represented as a chromosome, with genes corresponding to system parameters. The population of chromosomes is initialized with random or predefined parameter values to encompass a diverse set of potential solutions. Fitness evaluation assesses each chromosome's performance based on the defined objective functions, resulting in a vector of objective values. Non-dominated sorting categorizes solutions into different Pareto fronts, revealing trade-offs between objectives. A selection mechanism favors solutions on the Pareto front, employing elitist strategies to preserve the best solutions. Crossover and mutation operations create new offspring solutions, introducing variability. A replacement strategy combines offspring and existing solutions to form the next generation. Termination criteria determine when the optimization process stops, considering factors like reaching a maximum number of generations, achieving convergence, or obtaining a diverse set of Pareto optimal solutions. Result analysis involves extracting Pareto optimal solutions from the final Pareto front, offering decision-makers a diverse range of alternatives for the optimized configuration of the VARS.

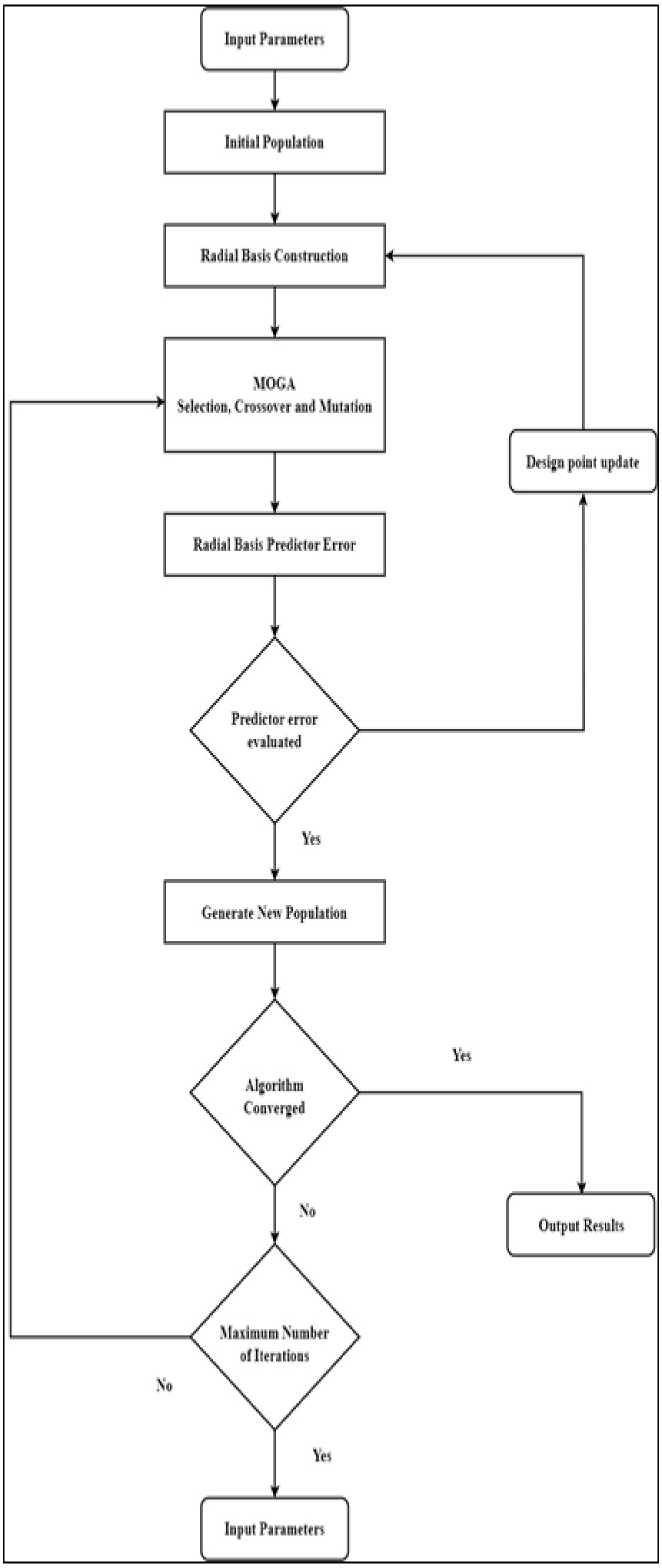

Fig 6 Schematic of the Multi-Objective Genetic Algorithm Technique

MOGA effectively addresses the multi-objective nature of optimization problems, providing a set of solutions that represent the trade-offs between conflicting objectives in the context of vapor absorption refrigeration systems.

Nedjah, De Macedo Mourelle, and Lizarazu (2022) investigate the feasibility of multi-objective optimization in refrigeration systems with cooling towers and chillers. The goal is to find operational setpoints balancing energy consumption reduction and tower effectiveness improvement for enhanced overall energy efficiency. The study employs evolutionary algorithms (SPEA2, NSGA-II, and Micro-GA) and analyzes Pareto fronts under two stopping criteria: fixed iterations (50) and fixed time (90 seconds). Results favor the SPEA2 algorithm with a 90-second stopping criterion. Future improvements could involve refining models for various chillers, exploring pump speed variations, incorporating frequency converters, estimating water consumption, and considering alternative optimization algorithms.

Nasruddin et al. (2019) modeled a university building with radiant cooling and VAV systems, assessing annual energy consumption and thermal comfort (PPD). Utilizing a multi-objective optimization approach, combining ANN and MOGA, optimal building operation was determined. The ANN achieved precise predictions (RMSE: 0.3 for energy consumption, 1 for PPD). Multi-objective optimization significantly improved HVAC operation for thermal comfort while maintaining low annual energy consumption compared to the base case design. The Pareto front offered diverse design alternatives, providing insights for effective control strategies in HVAC systems and serving as a reference for solving complex optimization problems in building designs.

In a different work, Sadeghi et al., (2015) designed an ejector refrigeration system using waste heat from a HCCI and performed multi-objective adjustment of energy efficiency and overall product cost of their system by employing the GA. With a 0.85% rise in the unit cost of the finished product, multi-objective optimization led to a 15.18% increase in energetic efficiency.

Jamali, Ahmadi, and Jaafar (2014) propose a novel combined cycle merging the Brayton power cycle and the ejector expansion refrigeration cycle, offering simultaneous heating, cooling, and power generation. Operated by low-temperature heat sources with CO_2 as the working fluid, the system achieves a 46% energy savings compared to separate generation of cooling, power, and hot water. The study includes a comprehensive parametric investigation, exergy analysis, and system optimization using a multi-objective evolutionary genetic algorithm.

- *Nondominated Sorting Genetic Algorithm II (NSGA II)*

The Nondominated Sorting Genetic Algorithm II (NSGA-II) is a multi-objective optimization algorithm that efficiently handles problems with multiple conflicting objectives.

In the optimization of VARS using NSGA-II, a multi-objective evolutionary algorithm, the process encompasses several key steps. Multiple objective functions are defined to capture diverse aspects of system performance, such as maximizing the COP, minimizing energy consumption, and optimizing exergetic efficiency. Each potential solution is represented as a chromosome, with genes corresponding to system parameters like temperatures and pressures. The population of chromosomes is initialized with random or predefined parameter values. Fitness evaluation assesses each chromosome's performance based on the defined objective functions, resulting in a vector of objective values. Nondominated sorting categorizes solutions into different fronts, revealing Pareto fronts that indicate trade-offs between objectives. Crowding distance assignment helps maintain diversity within each Pareto front. A selection mechanism prioritizes solutions on the Pareto front with lower crowding distances. Crossover and mutation operations create new offspring solutions, introducing variability. A replacement strategy combines offspring and existing solutions to form the next generation. Termination criteria determine when the optimization process stops, considering factors like reaching a maximum number of generations or achieving convergence. Result analysis involves extracting Pareto optimal solutions from the final Pareto front, offering decision-makers a diverse set of alternatives for the optimized configuration of the VARS.

NSGA-II efficiently explores the trade-off solutions in the objective space, offering a diverse set of solutions for decision-makers to choose from in the context of VARS.

Sai and Rao (2022) utilize optimization methods for STHE design cost reduction. Conventional techniques like PSO and ARGA face limitations such as lower convergence and susceptibility to local optima. This study proposes a hybrid approach, combining NSGA II and PSO, to enhance cost reduction in STHE design. The hybrid method incorporates total cost and overall heat transfer as objective functions for improved performance. NSGA II ensures robust exploration, while PSO exploits the best solution of NSGA II, escaping local optima. Tested on three cases, the hybrid NSGA II-PSO method outperforms existing optimization methods, achieving a 4.85% and 1.51% reduction in total cost for cases 1 and 2, respectively, compared to the ARGA method.

Zendehboudi et al. (2019) extensively investigate R450A behavior in refrigeration systems and introduce a hybrid multi-objective optimization model, combining the response surface method and non-dominated sorted genetic algorithm II. Regression analysis confirms strong agreement between experimental data and quadratic polynomial models (coefficient of determination > 0.97). Optimal results for the first scenario include an 18.39% reduction in motor-compressor electrical power consumption, a 53.51% decrease in discharge temperature, and a 215.57% increase in refrigerant mass flow rate. These improvements occur with specified changes in middle evaporator temperature, middle condenser temperature, superheating degree, and subcooling degree.

Keshtkar and Talebizadeh (2017) aimed to conduct a multi-objective optimization of a cooling water package, integrating exergetic, economic, and environmental (3E) analyses through the utilization of the NSGA-II. The study involved modeling several objective scenarios and decision factors within EES software, resulting in a collection of MINLP optimization problems. It primarily concentrated on the compression refrigeration cycle that supplies chilled water for equipment cooling. The study examined four distinct optimization scenarios, including multi-objective optimization and single-objective optimization for thermodynamic, economic, and environmental effects. By reducing exergy destruction from 264.8 kW to 127.6 kW and improving the performance coefficient from 3.872 to 7.088, multi-objective optimization was able to accomplish the most simultaneous satisfaction of 3E results, according to a comparative analysis. Furthermore, the cost of producing cold water dropped from 117.5 $/hr to 87.19 $/hr, and the amount of NOx emissions decreased from 4958 kg per year to 2645 kg per year. Multi-objective optimization was ultimately applied, and the refinery's overall cost was noticeably improved by 25.8%.

Yang and Cheng (2014) introduce a novel multi-objective global optimization method using a dynamic model of refrigerators and the Genetic Algorithm NSGA-II to enhance household refrigerator performance. The study optimizes a novel refrigerator with heat-storage condensers and a conventional refrigerator, minimizing total cost and energy consumption per 24 hours. Both refrigerators show improved performance after optimization. The novel refrigerator outperforms the conventional one, achieving energy savings of 20% to 26% under the same total cost and cost savings of $1.8 to $3.4 under the same energy consumption per 24 hours.

IV. CONCLUSION

In conclusion, this comprehensive review has elucidated the application of advanced computational intelligence approaches in the optimization of vapor absorption refrigeration systems. The studied techniques, including SA, DE, CRO, HTS, MOGA, and NSGA-II, have demonstrated remarkable efficacy in addressing the intricate challenges posed by the complex, nonlinear, and multi-modal nature of modern refrigeration systems.

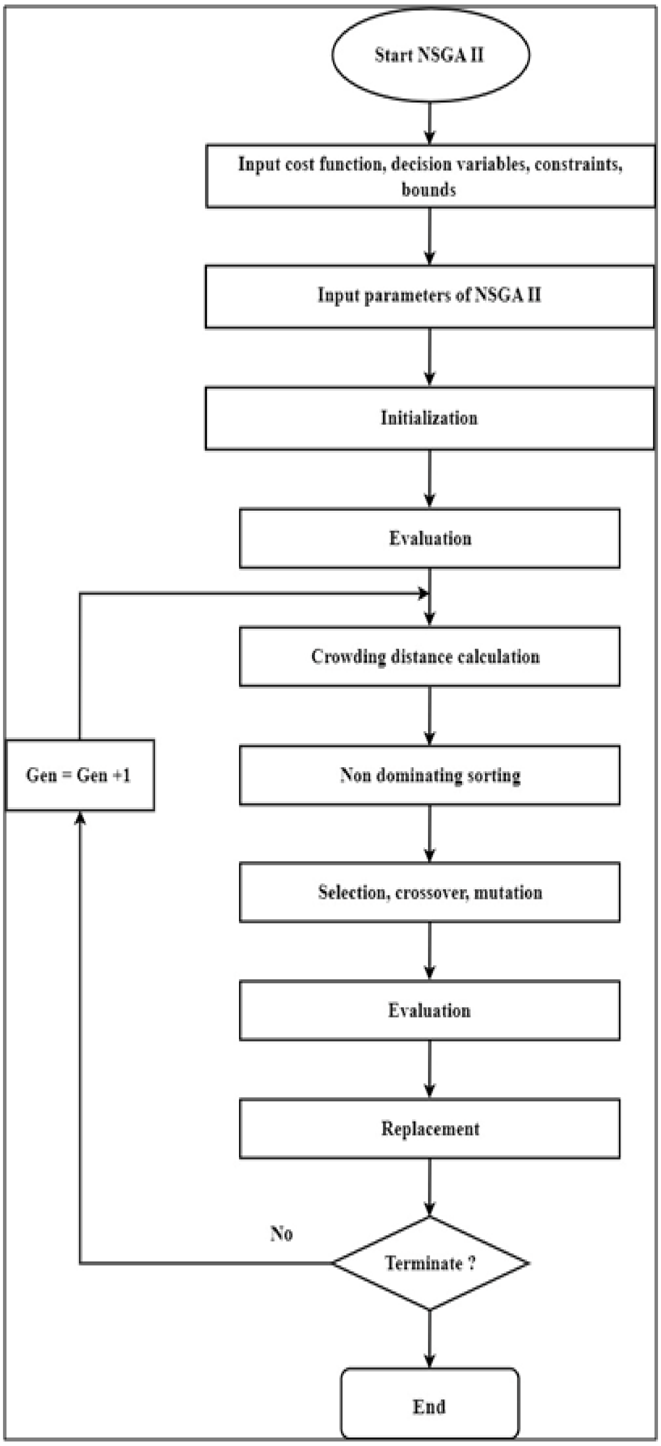

Fig 7 Schematic of the Non Dominated Sorted Genetic Algorithm II Technique

The literature survey emphasized the significance of these computational techniques in achieving optimal configurations for VARS, with a focus on key performance indicators such as COP, energy consumption, exergetic efficiency, and cooling capacity. Notably, the application of these approaches has paved the way for substantial advancements in overcoming the environmental impact associated with refrigeration technologies, aligning with global initiatives such as the Paris Conference Agreement on environmental crisis mitigation.

Each computational intelligence approach brings its unique strengths to the optimization process. Simulated Annealing, inspired by metallurgical annealing processes, offers a global search strategy, while Differential Evolution leverages population dynamics to navigate complex solution spaces. Chemical Reaction Optimization mimics chemical reactions to diversify exploration, and Heat Transfer Search simulates heat transfer processes to explore potential configurations. Multi-Objective Genetic Algorithm and Nondominated Sorting Genetic Algorithm II excel in handling multiple conflicting objectives, providing decision-makers with Pareto optimal solutions and trade-offs.

The convergence of these computational intelligence techniques has demonstrated their collective ability to yield optimal and sustainable solutions for vapor absorption refrigeration systems. As the global demand for energy-efficient and environmentally friendly refrigeration technologies continues to escalate, the insights provided by this review pave the way for future research directions. The integration of these approaches, coupled with ongoing advancements in artificial intelligence and optimization algorithms, holds great promise for addressing the evolving challenges in the field and contributing to the realization of more sustainable refrigeration practices.

FUTURE SCOPE OF WORK

The exploration of computational intelligence approaches for the optimization of vapor absorption refrigeration systems has uncovered promising avenues for future research. The following outlines key areas that merit attention in advancing the field:

- *Hybridization of Techniques:*

Investigate the potential benefits of combining multiple computational intelligence techniques in hybrid frameworks. Hybridization can harness the strengths of different algorithms, offering enhanced optimization capabilities and potentially addressing challenges associated with specific techniques.

- *Machine Learning Integration:*

Explore the integration of machine learning algorithms, such as neural networks and deep learning, with computational intelligence techniques. This interdisciplinary approach may provide more adaptive and data-driven optimization strategies, particularly in addressing uncertainties and dynamic conditions in refrigeration systems.

- *Real-Time Implementation:*

Shift focus towards real-time implementation of optimization strategies. Developing algorithms that can adapt and optimize refrigeration systems dynamically in response to changing operational conditions will be crucial for enhancing energy efficiency and overall system performance.

- *Robustness and Scalability:*

Assess the robustness and scalability of existing computational intelligence techniques. Research efforts should aim to develop algorithms that can handle larger and more complex refrigeration systems, ensuring applicability to industrial-scale operations.

- *Multi-Objective Optimization Metrics:*

Further investigate the development of novel multi-objective optimization metrics that align with specific industry requirements. Customized metrics could better capture the nuances of performance in vapor absorption refrigeration systems, leading to more tailored and effective optimization strategies.

- *Sensitivity Analysis and Uncertainty Modeling:*

Incorporate sensitivity analysis and uncertainty modeling techniques to enhance the reliability of optimization outcomes. Understanding the impact of uncertainties in parameters and environmental conditions will contribute to the robustness of the developed optimization frameworks.

- *Integration with IoT and Industry 4.0:*

Explore the integration of computational intelligence approaches with Internet of Things (IoT) technologies and Industry 4.0 principles. This integration can enable smarter, connected refrigeration systems that leverage real-time data and communication for adaptive and intelligent decision-making.

- *Lifecycle Analysis and Environmental Impact:*

Extend the scope to include lifecycle analysis and environmental impact assessments. Beyond optimizing operational parameters, considering the broader environmental footprint of refrigeration systems will contribute to sustainable practices and align with global environmental goals.

- *Validation through Experimental Studies:*

Validate computational intelligence approaches through experimental studies and field trials. Real-world validation will enhance the applicability of optimized solutions and bridge the gap between theoretical developments and practical implementation.

- *Interdisciplinary Collaboration:*

Encourage interdisciplinary collaboration between experts in computational intelligence, refrigeration engineering, environmental science, and industrial practitioners. This collaborative approach can bring diverse perspectives to the optimization problem and foster holistic solutions.

By delving into these future research directions, the scientific community can contribute to the continued evolution of computational intelligence approaches, advancing the optimization of vapor absorption refrigeration systems towards greater efficiency, sustainability, and adaptability in the face of emerging challenges.

APPENDIX

➢ *Acronyms*

- SA Simulated Annealing.
- DE Differential Evolution.
- SADE Self Adaptive Differential Evolution.
- HTS Heat Transfer Search.
- CRO Chemical Reaction Optimization.
- MOGA Multi-Objective Genetic Algorithm.
- NSGAII Nondominated Genetic Algorithm II
- COP Coefficient of Performance.
- CRS Cascade Refrigeration System.
- PSO Particle Swarm Optimization.
- EES Engineering Equation Solver.
- CI Computational Intelligence.
- VARS Vapor Absorption Refrigeration System.
- HCCI Homogenous Charge Compression Ignition.
- MINLP Mixed Integer Nonlinear Programming.
- OCL Optimal Chiller Loading.
- LDAC Liquid Desiccant Air Conditioning.
- VAV Variable Air Volume.
- STHE Shell and Tube Heat Exchanger.
- ARGA Adaptive Range Genetic Algorithm.
- TS Tabu Search
- DCRO Discrete Chemical Reaction Optimization.

REFERENCES

[1]. Chen, Danlei, Yiqing Luo, and Xin Yuan. 2023. "Cascade Refrigeration System Synthesis Based on Hybrid Simulated Annealing and Particle Swarm Optimization Algorithm." Chinese Journal of Chemical Engineering 58: 244–55. https://doi.org/10.1016/j.cjche.2022.10.021.
[2]. Mahadzir, Shuhaimi, and Rasel Ahmed. 2021. "Parametric Optimization of a Two Stage Vapor Compression Refrigeration System by Comparative Evolutionary Techniques." E3S Web of Conferences 287: 03002. https://doi.org/10.1051/e3sconf/202128703002.
[3]. Maakala, Viljami, Mika Järvinen, and Ville Vuorinen. 2018. "Optimizing the Heat Transfer Performance of the Recovery Boiler Superheaters Using Simulated Annealing, Surrogate Modeling, and Computational Fluid Dynamics." Energy 160: 361–77. https://doi.org/10.1016/j.energy.2018.07.002.
[4]. Chan, Tien-Shun, Yung-Chung Chang, and Jian-He Huang. 2017. "Application of Artificial Neural Network and Genetic Algorithm to the Optimization of Load Distribution for a Multiple-Type-Chiller Plant." Building Simulation 10 (5): 711–22. https://doi.org/10.1007/s12273-017-0363-2.
[5]. Kong, Dehao, Xiaohong Yin, Xi Ding, Ning Fang, and Peiyong Duan. 2021. "Global Optimization of a Vapor Compression Refrigeration System with a Self-Adaptive Differential Evolution Algorithm." Applied Thermal Engineering 197: 117427. https://doi.org/10.1016/j.applthermaleng.2021.117427.
[6]. Lin, Chang Ming, Cheng-Shong Wu, Ko Ying Tseng, Chih Chiang Ku, and Sheng-Fuu Lin. 2019. "Applying Two-Stage Differential Evolution for Energy Saving in Optimal Chiller Loading." Energies 12 (4): 622. https://doi.org/10.3390/en12040622.
[7]. Wang, Xinli, Wenjian Cai, and Xiaohong Yin. 2017. "A Global Optimized Operation Strategy for Energy Savings in Liquid Desiccant Air Conditioning Using Self-Adaptive Differential Evolutionary Algorithm." Applied Energy 187: 410–23. https://doi.org/10.1016/j.apenergy.2016.11.073.
[8]. Lee, Wen-Shing, Yi-Ting Chen, and Yu-Cheng Kao. 2011. "Optimal Chiller Loading by Differential Evolution Algorithm for Reducing Energy Consumption." Energy and Buildings 43 (2–3): 599–604. https://doi.org/10.1016/j.enbuild.2010.10.028.
[9]. Mansuriya, Kiran, Vivek Patel, Nishith B. Desai, and Nilesh M. Vora. 2020. "A Performance Evaluation of the Ejector Refrigeration System Based on Thermo-Economic Criteria through Multi-Objective Approach." Clean Technologies and Environmental Policy 23 (4): 1087–1103. https://doi.org/10.1007/s10098-020-01884-1.
[10]. Patel, Vivek, Deep Panchal, Anil S. Prajapati, Anurag Mudgal, and Philip A. Davies. 2019. "An Efficient Optimization and Comparative Analysis of Cascade Refrigeration System Using NH_3/CO_2 and C_3H_8/CO_2 Refrigerant Pairs." International Journal of Refrigeration 102: 62–76. https://doi.org/10.1016/j.ijrefrig.2019.03.001.
[11]. Pattanaik, Jagat Kishore, Mousumi Basu, and Deba Prasad Dash. 2019. "Heat Transfer Search Algorithm for Combined Heat and Power Economic Dispatch." Iranian Journal of Science and Technology, Transactions of Electrical Engineering 44 (2): 963–78. https://doi.org/10.1007/s40998-019-00280-w.
[12]. Patel, Vivek, and Vimal Savsani. 2015. "Heat Transfer Search (HTS): A Novel Optimization Algorithm." Information Sciences 324: 217–46. https://doi.org/10.1016/j.ins.2015.06.044.
[13]. Hadidi, A. (2017). A novel approach for optimization of electrically serial two-stage thermoelectric refrigeration systems using chemical reaction optimization (CRO) algorithm. Energy, 140, 170–184. https://doi.org/10.1016/j.energy.2017.08.087.
[14]. Hadidi, Amin. 2017. "Optimization of Electrically Separated Two-Stage Thermoelectric Refrigeration Systems Using Chemical Reaction Optimization Algorithm." Applied Thermal Engineering 123: 514–26. https://doi.org/10.1016/j.applthermaleng.2017.05.141.

[15]. Li, J., & Pan, Q. (2012). Chemical-reaction optimization for flexible job-shop scheduling problems with maintenance activity. Applied Soft Computing, 12(9), 2896–2912. https://doi.org/10.1016/j.asoc.2012.04.012.
[16]. Lam, A. Y. S., & Li, V. O. K. (2010). Chemical-Reaction-Inspired metaheuristic for optimization. IEEE Transactions on Evolutionary Computation, 14(3), 381–399. https://doi.org/10.1109/tevc.2009.2033580.
[17]. Nedjah, Nadia, Luiza De Macedo Mourelle, and Marcelo Silveira Dantas Lizarazu. 2022. "Evolutionary Multi-Objective Optimization Applied to Industrial Refrigeration Systems for Energy Efficiency." Energies 15 (15): 5575. https://doi.org/10.3390/en15155575.
[18]. Nasruddin, Nasruddin, Sholahudin, Pujo Satrio, T.M.I. Mahlia, Niccolò Giannetti, and Kiyoshi Saito. 2019. "Optimization of HVAC System Energy Consumption in a Building Using Artificial Neural Network and Multi-Objective Genetic Algorithm." Sustainable Energy Technologies and Assessments 35: 48–57. https://doi.org/10.1016/j.seta.2019.06.002.
[19]. Sadeghi, Mohsen, S.M.S. Mahmoudi, and Rahim Khoshbakhti Saray. 2015. "Exergoeconomic Analysis and Multi-Objective Optimization of an Ejector Refrigeration Cycle Powered by an Internal Combustion (HCCI) Engine." Energy Conversion and Management 96: 403–17. https://doi.org/10.1016/j.enconman.2015.02.081.
[20]. Jamali, Arash, Pouria Ahmadi, and Mohammad Nazri Mohd. Jaafar. 2014. "Optimization of a Novel Carbon Dioxide Cogeneration System Using Artificial Neural Network and Multi-Objective Genetic Algorithm." Applied Thermal Engineering 64 (1–2): 293–306. https://doi.org/10.1016/j.applthermaleng.2013.11.071.
[21]. Sai, Juluru Pavanu, and B. Nageswara Rao. 2022. "Non-Dominated Sorting Genetic Algorithm II and Particle Swarm Optimization for Design Optimization of Shell and Tube Heat Exchanger." International Communications in Heat and Mass Transfer 132: 105896. https://doi.org/10.1016/j.icheatmasstransfer.2022.105896.
[22]. Zendehboudi, Alireza, Adrián Mota-Babiloni, Pavel Makhnatch, R. Saidur, and Sadiq M. Sait. 2019. "Modeling and Multi-Objective Optimization of an R450A Vapor Compression Refrigeration System." International Journal of Refrigeration 100: 141–55. https://doi.org/10.1016/j.ijrefrig.2019.01.008.
[23]. Keshtkar, Mohammad Mehdi, and Pouyan Talebizadeh. 2017. "Multi-Objective Optimization of Cooling Water Package Based on 3E Analysis: A Case Study." Energy 134: 840–49. https://doi.org/10.1016/j.energy.2017.06.085.
[24]. Yang, Xudong, and Wen-Long Cheng. 2014. "Multi-Objective Optimization of Household Refrigerator with Novel Heat-Storage Condensers by Genetic Algorithm." Energy Conversion and Management 84: 550–61. https://doi.org/10.1016/j.enconman.2014.04.086.