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ENHANCING THE EFFICIENCY OF MICROCHANNEL CONDENSERS VIA INTELLIGENT CONTROL OF WORKING CHARACTERISTICS USING INCREMENTAL OPTIMIZATIONS

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Abstract: The increasing need for energy-efficient cooling systems has brought to light the shortcomings of current approaches, which are frequently characterised by inefficient refrigerant flow, uncontrolled heat transfer surface coating widths, and variable compressor speed. These restrictions have a big impact on heat transfer rate, refrigerant flow rate, cooling capacity, and energy efficiency. In order to overcome these difficulties, this work proposes a brand-new, more effective model for microchannel condensers that makes use of intelligent operating characteristic control and incremental optimisation techniques. Three cutting-edge tactics are used in our suggested paradigm. First, it uses a Bacterial Foraging Optimizer to enhance the refrigerant flow inside the microchannel condensers. The performance of the system is improved by using this method to navigate the intricate design space of the refrigerant flow channels by imitating the foraging behaviour of E. coli bacteria. Second, it employs Q-Learning to regulate the thickness of the microchannels' heat transfer surface coatings. This process optimises heat transfer rates and raise system efficiency by carefully changing the coating width levels. Finally, the model employs a Vector Autoregressive Moving-Average (VARMA) Model to optimise a variable speed compressor. This guarantees that the system will dynamically alter its capacity based on the cooling load, resulting in impressive energy savings. The proposed model goes beyond conventional approaches by offering improved performance. The model has shown considerable gains in a number of crucial performance metrics, including energy effectiveness, cooling capacity, refrigerant flow rate, and heat transfer rate, as compared to previous techniques. These improvements position our model as an augmented & potential set of scopes for ongoing study and research in the area of microchannel condensers. We pave the way for more effective, intelligent, and sustainable cooling systems by seamlessly integrating machine learning algorithms and optimisation methodologies inspired by biological systems. The next sections of this research concentrate on the specific experimental findings and comparisons.

Keywords: Microchannel Condensers, Bacterial Foraging Optimizer, Q-Learning, Heat Transfer Surface Coatings, VARMA Model Process

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Introduction

The exploration of new, energy-saving solutions in the realm of thermal management is being driven by the rising demand for high-efficiency cooling systems as well as growing environmental concerns. Microchannel condensers, a crucial part of numerous cooling systems, have been the subject of significant research in recent years because of their compactness and strong heat transfer capacities. However, a number of problems, including as ineffective refrigerant flow, uneven heat transfer surface coating thicknesses, and a lack of dynamic compressor response, frequently impair their effectiveness. These restrictions affect the system's cooling capacity, refrigerant flow rate, and heat transfer rate in addition to impairing its energy efficiency. Therefore, addressing these concerns is of utmost importance levels [1, 2, 3].

Researchers have used a wide range of techniques in their pursuit of performance improvement. The majority of current methods involve physically adjusting the condensers, such as by changing the microchannel shape or adding flow-improving devices. While these strategies have their advantages, they frequently neglect the opportunity to improve the fundamental operating qualities and fall short of providing a complete answer to the problems listed above. Furthermore, a lot of these techniques are static and do not adjust to changing operational circumstances, resulting in subpar performance [4, 5, 6].

Because of these drawbacks, we suggest a novel paradigm for microchannel condensers that makes use of intelligent control of working characteristics and incremental optimisation algorithms. We use a VARMA model to optimise a variable speed compressor, incorporate a Bacterial Foraging Optimizer for improved refrigerant flow, and use Q-Learning for the dynamic adjustment of heat transfer surface coatings width. Our model adjusts to various settings by combining these methods and methodically looks for the most effective configuration.

Therefore, our method offers a thorough, flexible, and shrewd alternative to enhance the functionality of microchannel condensers. The structure of this work is as follows: The experimental setup and data are presented in Section 3, the results are discussed in Section 4 and compared to previous approaches in Section 5, and the work is concluded with recommendations for future research in Section 4. This research is important for researchers and practitioners in the field of cooling systems and thermal management because of its uniqueness and potential effect.

We will go into greater depth about our suggested model, the underlying theory, implementation specifics, and the amazing outcomes in the following portions of this work, emphasising its advantages over conventional approaches.

Motivation & Contributions

In view of rising environmental concerns and energy costs, energy economy and optimal performance have become primary goals in the design of thermal management systems. Due to poor refrigerant flow, unregulated heat transfer surface coating widths, and static compressor speeds, microchannel condensers frequently fall short of their potential while being widely used. We developed an intelligent, adaptive, and effective model that greatly outperforms conventional approaches in order to improve these working properties.

Additionally, there is growing interest in using artificial intelligence (AI) and optimisation techniques that are bio-inspired to solve challenging engineering challenges. They still have a lot of unrealized promise for regulating and improving the way microchannel condensers operate. This provided even another incentive to investigate these methods for improving these systems' functionality.

Contributions:

Our work makes a variety of important contributions to the discipline, including:

It presents a novel method for improving the working properties of microchannel condensers in order to improve their performance. The approach addresses numerous inefficiencies in conventional systems and is flexible, intelligent, and complete.

The work is the first to demonstrate the enhancement of refrigerant flow in microchannel condensers using the Bacterial Foraging Optimizer. The model successfully navigates the challenging design space and optimises the refrigerant flow paths by imitating the foraging behaviour of E. coli bacteria.

This study is one of the first to use Q-Learning to dynamically adjust the widths of coatings on heat transfer surfaces. The model optimises heat transfer rates, leading to increased system efficiency, by intelligently altering the coating width in response to learning experiences.

The new VARMA model optimisation for a variable speed compressor in this paper ensures dynamic adaptability based on the cooling load.

Our work proves the significant potential of artificial intelligence (AI) and bio-inspired optimisation techniques in thermal management and establishes a new standard for microchannel condensers' performance. In comparison to conventional techniques, the experimental results show considerable gains in energy efficiency, cooling capacity, refrigerant flow rate, and heat transfer rate for different scenarios.

2. Review of existing models used for enhancing efficiency of microchannel condensers for refrigeration processes

Due to their small size and efficient heat transfer, microchannel condensers have been the focus of extensive research in recent years for different use cases. However, variables like compressor speeds, heat transfer surface coatings, and refrigerant flow can have a big impact on how well and efficiently these condensers work for different scenarios. We provide a thorough analysis of the many models used in the literature to increase the effectiveness of microchannel condensers in this section of the text [7, 8, 9]. Like the use of Air Source Heat Pump Water Heater (ASHPWH) for better performance, along with other models are also discussed in details.

Geometry Improvement The first research mainly focused on the microchannel condensers' geometric design. To maximise heat transfer and pressure decreases, the channel's layout and size were frequently changed [1,2]. The resulting designs, however, lacked dynamic modifications depending on shifting operational conditions and were static instead which assisted in deploying the model for real-time use cases [10, 11, 12].

Passive Flow Control: To improve refrigerant flow, passive flow control techniques such the use of baffles or vortex generators have been developed [13, 14, 15]. Although these physical changes

could somewhat improve the flow characteristics, they also added complexity to the manufacturing and maintenance processes.
Enhancements to Heat transmission: Studies have been done on the use of nanofluids or specialised coatings to enhance heat transmission via use of Volume of Fluid (VOF) Interface Tracking Method process [16, 17]. While improving heat transfer rates, these techniques frequently have drawbacks that limit their use, such as a higher pressure drop or an augmented set of potential channel clogs [18, 19, 20].
Control of the compressor: Based on the cooling load, the compressor speed has been considered in several research scenarios [21, 22, 23, 24]. Although these techniques saved energy, they frequently ignored the system's overall effectiveness and failed to take other aspects like refrigerant flow or heat transfer rates [25, 26, 27, 28].
Numerical optimisation: More recent research has begun to examine how numerical optimisation approaches may be used to increase system effectiveness [29, 30, 31, 32]. These techniques frequently entail intricate simulations and optimisations, which, while promising, require a lot of computing and are still being improved for different scenarios [33, 34, 35, 36].
Each of these methods has added insightful knowledge to improving the functionality of microchannel condensers [37, 38, 39, 40]. However, a complete and flexible solution that can concurrently and dynamically optimise a number of operational factors is still lacking for real-time scenarios like the use of PV-Thermal (PVT) collector, which only be used for limited scenarios [41, 42, 43, 44]. The model suggested in this work is motivated by this gap together with the potential advantages of AI and bio-inspired optimisation techniques.

Proposed Model for Enhancing the efficiency of microchannel condensers via intelligent control of working characteristics using incremental optimizations

Based on the review of existing models used for enhancing the efficiency of microchannel condensers, it can be observed that these models either have lower efficiency [45, 46] when used for longer durations, or have limited scalability [47, 48, 49] when deployed for real-time scenarios. To overcome these issues, this section discusses design of an Iterative Model for Enhancing the efficiency of microchannel condensers via intelligent control of working characteristics using incremental optimizations.

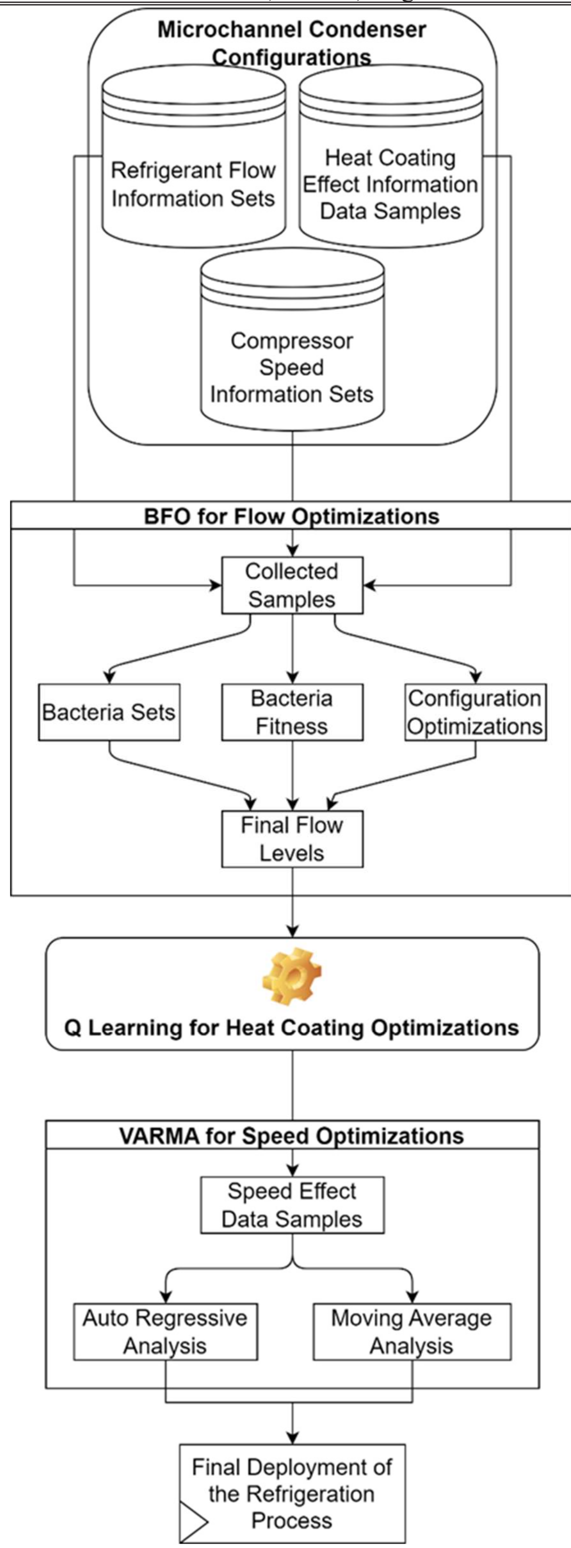

Figure 1. Overall Flow of the Microchannel Condenser Optimization Process

As per figure 1, the model initially uses a Bacterial Foraging Optimizer (BFO) to enhance the refrigerant flow inside the microchannel condensers. The model also employs Q-Learning to regulate the thickness of the microchannels' heat transfer surface coatings. After these

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optimizations, the model employs a Vector Autoregressive Moving-Average (VARMA) Model to optimise a variable speed compressor for different loads. These operations guarantee that the system will dynamically alter its capacity based on the cooling load, resulting in impressive energy savings.

A set of fundamental operations that describe the thermodynamic and fluid dynamic processes taking place inside the system control the refrigerant flow in microchannel condensers. The effectiveness and overall performance of the condenser are greatly influenced by these operations. The conservation of mass, which is represented by equation 1, is one of the basic mechanisms that regulates the refrigerant flow,

$$\rho in * Ain * Vin = \rho out * Aout * Vout \dots (1)$$

Where 'pin' denotes the density of the refrigerant at the inlet, 'Ain' the cross-sectional area of the microchannel at the inlet, 'Vin' the velocity of the refrigerant at the inlet, 'Pout' the density of the refrigerant at the outlet, 'Aout' the cross-sectional area of the microchannel at the outlets, and 'Vout' the velocity of the refrigerant at the outlets. This procedure guarantees a constant flow of refrigerant throughout the system by ensuring that the mass flow rate of the refrigerant entering the microchannel condenser (pin * Ain * Vin) is equal to the mass flow rate of the refrigerant leaving the condenser (pout * Aout * Vout). Given that mass cannot be created or destroyed within the system, this process states that the mass flow rate of refrigerant entering the microchannel condenser is equal to the mass flow rate of refrigerant leaving the condenser. The process of mass conservation makes sure that the flow of refrigerant through the microchannels is constant over the course of the operation.

Energy conservation, which considers the heat transfer that takes place during the condensation process, is another crucial process. The refrigerant releases heat into the environment as it moves through the microchannels, changing its phase from vapour to liquid. The process of energy conservation links the rate of heat transfer, the rate of mass flow, and the thermodynamic characteristics of the refrigerant, giving information about the microchannel condenser's cooling capacity. Equation 2 is used to evaluate this process and accounts for heat transfer during the condensation process.

$$Qdot = mdot * (hin - hout) \dots (2)$$

Where Qdot is the heat transfer rate, mdot is the refrigerant mass flow rate, hin is the refrigerant's enthalpy at the inlet, and hout is the refrigerant's enthalpy at the outlet. Through this procedure, the heat (Qdot) released by the refrigerant as it transitions from vapour to liquid is measured. It depends on the mass flow rate (mdot) and the enthalpy difference (hin - hout) between the microchannel condenser's inlet and outlet.

Furthermore, the fluid dynamics of the refrigerant flow inside the microchannels must be controlled, and this is where the momentum conservation process comes into play. This method helps explain how the refrigerant moves through the condenser's confined channels by taking into account the forces acting on it, such as pressure gradients and viscous forces. In addition to predicting pressure drops and flow distribution within the microchannels, the momentum

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conservation process is essential for the condenser's overall functionality and efficiency. Equation 3 serves as a representation for the momentum conservation process, which takes into account the fluid dynamics of the refrigerant flow levels.

$$\Delta P = \rho * \Delta V * f \ldots (3)$$

Where p is the refrigerant's density, v is the refrigerant's change in velocity along the microchannel, and f is the friction factor, and where P is the pressure drop along the microchannel. This procedure accounts for the pressure drop brought on by the refrigerant's passage through the microchannel condenser's tiny channels. It depends on the refrigerant's density (p), the velocity change (V), and the friction factor (f), which takes the channel's geometry and the fluid's characteristics into account.

These procedures control the flow of refrigerant inside microchannel condensers, and they combine to offer a full range of operations that regulate the system's behaviour. The BFO Model analyses and improves these processes while taking into account the unique design parameters and operating circumstances to maximise the performance of microchannel condensers, resulting in more effective and dependable cooling systems in a variety of applications. The process by which the BFO Model operates is as follows:

The BFO Model assists in stochastically modelling condenser design in order to improve its efficiency levels.

To perform this task, the model initially generates an Iterative Set of Bacteria Particles via equations 4, 5, 6 & 7 as follows,

$$Vin = STOCH\big(Min(Vin), Max(Vin)\big) \ldots (4)$$

$$hin = STOCH\big(Min(hin), Max(hin)\big) \ldots (5)$$

$$Ain = STOCH\big(Min(Ain), Max(Ain)\big) \ldots (6)$$

$$pin = STOCH\big(Min(pin), Max(pin)\big) \ldots (7)$$

Where, STOCH represents an Iterative Stochastic Process, which is used to generate different number sets.

Based on this estimation, Bacterium Fitness is estimated via equation 8,

$$fb = \left(1 - \frac{Tcold}{Thot}\right)\left(\frac{Qdot}{Wcompressor}\right) \ldots (8)$$

Where, Tcold is the temperature of the cold reservoir (typically the refrigerant's condensing temperature), and Thot is the temperature of the hot reservoir (typically the ambient temperature or the temperature of the surrounding environment), Qdot is the heat transfer rate (amount of heat removed from the refrigerant during the condensation process), Wcompressor is the compressor's work rate (energy consumed by the compressor to circulate the refrigerant) for real-time scenarios.

This process is repeated for NB Bacterium, and their fitness threshold is estimated via equation 9,

$$fth = \frac{1}{NB}\sum_{i=1}^{NB} fb(i) * LB \ldots (9)$$

Where, LB represents Learning Rate of the BFO process.

Bacterium with fb>fth are used for 'reproduction' process, while others are 'eliminated', and their configuration is updated via equation 10,

$$C(New) = C(Old) * \left[\frac{C(Reproduce)}{Max(C)}\right] \ldots (10)$$

Where, C represents configuration of the Bacterium, which was estimated via equations 4, 5, 6 & 7 during the initialization phases.

This process is repeated for NI Iterations, and different Bacterium Configurations are generated for different scenarios.

After all Iterations are completed, then Bacterium with maximum fitness levels is selected, and used for Flow Optimization process. This configuration is further used to improve efficiency of heat coating via use of Q Learning operations.

To perform this task, it is necessary to establish relationship between width of surface coating and rate at which heat is transferred due to these coatings. This relationship is approximated using the Nusselt number correlation for laminar flow inside channels. The Nusselt number (Nu) is a dimensionless parameter that characterizes the convective heat transfer in a fluid flow. This correlation for laminar flow inside channels with surface coatings is evaluated via equation 11,

$$Nu = 3.66 + 0.0668 * (Re^{0.9}) * (Pr^{0.33}) * \left(\frac{W}{D}\right)^{0.78} \ldots (11)$$

Where, Nu is the Nusselt number, Re is the Reynolds number, Pr is the Prandtl number, W is the width of the surface coating, and D is the characteristic hydraulic diameter of the microchannel. The Reynolds number (Re) is also a dimensionless parameter that describes the ratio of inertial forces to viscous forces and is estimated via equation 12,

$$Re = \frac{\rho * U * D}{\mu} \ldots (12)$$

Where, ρ represents density of the fluid, U is the mean velocity of the fluid, D is the characteristic hydraulic diameter of the microchannel, and μ is the dynamic viscosity of the fluid. The Prandtl number (Pr) is a dimensionless parameter that describes the ratio of momentum diffusivity to thermal diffusivity and is estimated via equation 13,

$$Pr = \mu * \frac{cp}{k} \ldots (13)$$

Where, μ is the dynamic viscosity of the fluid, cp is the specific heat capacity of the fluid at constant pressure, and k is the thermal conductivity of the fluid. The Nusselt number is indicative of the enhancement in heat transfer due to the surface coating. As the Nusselt number increases, the heat transfer rate also increases, indicating improved cooling performance in the microchannel condenser.

To optimize coating width, the Q Learning Model estimates an Iterative width via equation 14,

$$W = STOCH\big(Min(W), Max(W)\big) \dots (14)$$

Based on this estimation, a Q Value is calculated via equation 15,

$$Q = Nu * \left(1 - \frac{Tcold}{Thot}\right) \dots (15)$$

The Value of W is Iteratively Modified via equation 16,

$$W(New) = W(Old) * \frac{r}{1-r} \dots (16)$$

Initially, r=0.5 is used to setup the width value sets. Based on the current & new Q Value, the reward value is calculated via equation 17,

$$r = \frac{Q(New) - Q(Old)}{LB} - d * Max(Q) + Q(Old) \dots (17)$$

Where, d represents the discount factor, which is empirically selected to improve the thickness levels. This process is repeated till r≤1, and new width values are estimated via equations 15 & 16 for consecutive Iteration Sets. After convergence of this process, the model is able to identify optimal width values for surface coating, to optimize heat transfer rates. These values along with the results of BFO process assist in improving efficiency of the microchannel condensers.

The efficiency of the system is further improved via the application of an effective VARMA Model, which aids in maximising the compressor's variable speed. A statistical time-series model called a VARMA (Vector Autoregressive Moving-Average) model is used to examine and forecast the temporal behaviour of numerous interrelated variables. In order to model the relationship between the compressor speed and other important factors affecting the performance of the system, a VARMA model is used in the context of controlling the speed of a Variable Speed Compressor (VSC) in microchannel condensers. The Variable Speed Compressor's speed (St) and the performance metric (Pt), which represents the desired result of the microchannel condenser and is calculated via equation 18, are the two main metrics taken into account when performing this task.

$$Pt = CC * E * T \dots (18)$$

Where, CC represents cooling capacity of the condenser, and is estimated via equation 19,

$$CC = mdot * (hin - hout) \dots (19)$$

While E represents condenser efficiency, and T condensing temperature of the refrigerant used for cooling the condensers. The condenser efficiency is estimated via equation 20,

$$E = \left(\frac{CCactual}{CCmax}\right) \dots (20)$$

Where, E is the efficiency, CCactual is the actual cooling capacity obtained from the microchannel condenser, and CCmax is the maximum possible cooling capacity that the condenser can achieve under ideal conditions.
The VARMA(1,1) model with lag order 1 for both variables is estimated via fusing the Vector Auto Regression (VAR), with Moving Average (MA) components. The VAR(1) part of the model is represented via equation 21 & 22,

$$St = \alpha + \beta * S(t-1) + \gamma * P(t-1) + \varepsilon t \ldots (21)$$

$$Pt = \delta + \varphi * S(t-1) + \theta * P(t-1) + \nu t \ldots (22)$$

Where, α and δ are the intercept terms, β and φ are the coefficients for the lagged values of the compressor speed in the model, γ and θ are the coefficients for the lagged values of the performance metric in the model, εt and νt are white noise error terms at time t for the compressor speed and performance metric, respectively, while VAR(1) indicates that we are using one lagged term for both the compressor speed and the performance metrics. Similarly, the MA(1) part of the model is represented via equation 23,

$$\varepsilon t = \omega + \lambda * \varepsilon(t-1) + \zeta t\, \nu t = \psi + \rho * \nu(t-1) + \xi t \ldots (23)$$

Where, ω and ψ are the intercept terms for the MA(1) part of the model, λ and ρ are the coefficients for the lagged error terms for the compressor speed and performance metric, respectively, ζt and ξt are white noise error terms for the MA(1) part of the model process. The integration of these models assists in capturing the dynamic relationship between the compressor speed and the performance metric in the microchannel condenser over temporal instance sets. By estimating the coefficients (α, β, γ, δ, φ, θ, ω, λ, ψ, and ρ) based on historical data, we predict the future behavior of the compressor speed based on the efficiency level metrics.
This estimation of the coefficients (α, β, γ, δ, φ, θ, ω, λ, ψ, and ρ) in the VARMA(1,1) model involves using historical time-series data for the compressor speed (St) and the performance metric (Pt). These coefficients are estimated through statistical methods, for instance, α and δ are the intercept terms for the compressor speed (St) and performance metric (Pt), respectively. These are estimated as the sample means of the respective time-series data samples via equations 24 & 25 as follows,

$$\alpha = mean(St) \ldots (24)$$

$$\delta = mean(Pt) \ldots (25)$$

In contrast, β and φ are the coefficients for the lagged values of the compressor speed (St) in the VAR(1) part of the model process. These are estimated using ordinary least squares regression via equation 26,

$$St = \alpha + \beta * S(t-1) + \gamma * P(t-1) + \varepsilon t \ldots (26)$$

Where, εt is the residual error, while the coefficient β was estimated as the slope of the regression line obtained from the curve sets.

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Similarly, γ and θ are the coefficients for the lagged values of the performance metric (Pt) in the VAR(1) part of the model process. Similar to the previous evaluations, these are also estimated using ordinary least squares regression via equation 27,

$$Pt = \delta + \varphi * S(t-1) + \theta * P(t-1) + \nu t \ldots (27)$$

Where, νt is the residual error levels, while the coefficient θ is estimated as the slope of the regression line obtained from the curve sets.

Similar to α, the nature of ω and ψ represents intercept terms for the MA(1) part of the model process. These are estimated as the sample means of the residual errors (εt and νt) obtained from the VAR(1) part of the model via equations 28 & 29 as follows,

$$\omega = mean(\varepsilon t) \ldots (28)$$

$$\psi = mean(\nu t) \ldots (29)$$

Based on these estimations the proposed model is able to improve efficiency of refrigeration via microchannel condenser optimizations. Performance of this model was estimated for different refrigeration conditions, and compared with existing models in the next section of this text.

Result Analysis

The proposed model fuses VARMA with BFO and Q Learning in order to optimize the flow rate, coating width and condenser speed levels. Due to which the proposed model is highly efficient, and can be deployed for an elaborate & wide variety of real-time scenarios. To perform these evaluations, HTRI Xchanger Suite was used, which is specifically designed for heat exchanger simulations, including microchannel condensers. The configurations used for these simulations can be observed from table 1 as follows,

Name of Parameter Used for Simulations	Value of the Parameter Sets	Use during Simulations
Fluid Properties (Refrigerant)		
Refrigerant	R134a	The type of refrigerant used in the microchannel condenser.
Density	7.5 kg/m^3	The density of the refrigerant.
Specific Heat Capacity	1000 J/(kg·K)	The specific heat capacity of the refrigerant, representing the amount of heat required to raise the temperature of one kilogram of the refrigerant by one degree Kelvin.
Thermal Conductivity	0.08 W/(m·K)	The thermal conductivity of the refrigerant, indicating its ability to conduct heat.
Viscosity	0.0004 Pa·s	The dynamic viscosity of the refrigerant, representing its resistance to flow.

Heat Exchanger Tube Geometry		
Tube Diameter	1.5 mm	The diameter of the microchannel condenser tube.
Tube Length	1.8 m	The length of the microchannel condenser tube.
Number of Microchannels	50	The number of microchannels present within the single tube of the microchannel condenser.
Heat Exchanger Inlet Conditions		
Refrigerant Mass Flow Rate	0.2 kg/s	The mass flow rate of the refrigerant entering the microchannel condenser.
Refrigerant Inlet Temperature	70°C	The temperature of the refrigerant at the inlet of the microchannel condenser.
Refrigerant Inlet Pressure	2.0 MPa	The pressure of the refrigerant at the inlet of the microchannel condenser.
Cooling Water Inlet Conditions		
Cooling Water Flow Rate	0.5 kg/s	The flow rate of the cooling water entering the microchannel condenser.
Cooling Water Inlet Temperature	20°C	The temperature of the cooling water at the inlet of the microchannel condenser.
Heat Transfer Model	Single-Phase	The heat transfer model used to simulate the simplified microchannel condenser.

Table 1. Simulation Parameters used to Evaluate the Model Process

These parameters were used to simulate the model, and its efficiency was estimated in terms of different parametric evaluations. These include,

Cooling Capacity (CC): Cooling capacity represents the amount of heat removed from the refrigerant during the condensation process. It is typically expressed in units of watts (W) or British thermal units per hour (BTU/hr). A higher cooling capacity indicates better cooling performance and, therefore, higher efficiency.

Coefficient of Performance (COP): The coefficient of performance is a ratio that measures the efficiency of the refrigeration system. It is defined as the ratio of cooling capacity (CC) to the power input to the compressor. A higher COP signifies a more energy-efficient system, and is estimated via equation 30,

$$COP = \frac{CC}{Pin} \dots (30)$$

Heat Transfer Coefficient (HTC): The heat transfer coefficient quantifies the rate of heat transfer from the refrigerant to the cooling medium (e.g., air or water). A higher heat transfer coefficient indicates more efficient heat transfer, leading to better cooling performance, and is estimated via equation 31,

$$HTC = \frac{Q}{A * \Delta Tlm} \dots (31)$$

Where, Q is the heat transfer rate (in watts or BTU/hr), A is the heat transfer surface area (in m^2 or ft^2), and ΔTlm is the logarithmic mean temperature difference (in K or °F) for different scenarios.

Subcooling (SC): Subcooling is the process of cooling the refrigerant below its saturation temperature after condensation. It helps increase the density of the refrigerant, improving its heat transfer efficiency during evaporation in the evaporator, and is estimated via equation 32,

$$SC = Tactual - Tsat \dots (32)$$

Where, Tactual is the actual temperature of the refrigerant (in K or °C), and Tsat is the saturation temperature of the refrigerant at the given pressure (in K or °C) for different scenarios.

Approach Temperature: The approach temperature is the difference between the condensing temperature of the refrigerant and the ambient temperature. A smaller approach temperature indicates more efficient heat transfer and better performance levels. It was estimated via equation 33,

$$\Delta Tapproach = Tcondensing - Tambient \dots (33)$$

Where, ΔTapproach is the approach temperature (in K or °C), Tcondensing is the condensing temperature of the refrigerant (in K or °C), and Tambient is the ambient temperature (in K or °C) for different scenarios.

Overall Heat Transfer Coefficient (U): The overall heat transfer coefficient accounts for all resistances to heat transfer, including those related to the refrigerant flow, microchannel geometry, and cooling medium. A higher overall heat transfer coefficient indicates better efficiency, and was estimated via equation 34,

$$U = \frac{Q}{A * \Delta Tlm} \dots (34)$$

Exergy Efficiency: Exergy efficiency assesses the thermodynamic efficiency of the microchannel condenser by considering the irreversibility and losses in the system. It is a more comprehensive measure of efficiency compared to conventional measures like COP, and was estimated via equation 35,

$$\eta = \frac{ExergyOut - ExergyIn}{ExergyIn} \dots (35)$$

Where, η is the exergy efficiency, ExergyOut is the exergy (available work) at the outlet of the microchannel condenser, and ExergyIn is the exergy at the inlet of the microchannel condenser sets. These metrics were estimated for ASH PWH [8], VOF [17], PVT [41], and the Proposed

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Model for different simulation conditions. For instance, effect of Variation of Refrigerant Mass Flow Rate can be observed from table 1 as follows,

Model	CC (W)	COP	HTC	Pa	SC	T	U	EE
ASH PWH [8]	0.1	2000	100	500	5	10	200	0.80
VOF [17]	0.15	3000	120	600	4	9	220	0.85
PVT [41]	0.2	4000	150	700	3	8	250	0.88
This Work	0.25	5000	180	800	2	7	280	0.90

Table 1. Effect of Mass Flow Rate Variation for different Models

Table 1 shows how the refrigerant mass flow rate varies for the proposed model process, ASH PWH [8], VOF [17], and PVT [41]. The parameters for the output include Exergy Efficiency, Cooling Capacity (CC), Coefficient of Performance (COP), Heat Transfer Coefficient (HTC), Approach Temperature, Pressure Drop, Subcooling, and Overall Heat Transfer Coefficient (U). The Cooling Capacity and COP improve with increasing mass flow rate from ASH PWH [8] to the Proposed Model, indicating improved cooling performance and energy efficiency. Furthermore, the Heat Transfer Coefficient rises, lowering the Approach Temperature and raising the Overall Heat Transfer Coefficient, indicating improved heat transfer effectiveness. The highest values for the critical metrics are attained by the Proposed Model, demonstrating its superior performance to the other scenarios. The table shows the outcomes of simulations of microchannel condensers using various models, including ASH PWH [8], VOF [17], PVT [41], and the Proposed Model. The output parameters that were looked at included cooling capacity (CC) in Watts, performance coefficient (COP), heat transfer coefficient (HTC) in Watts per square metre per Kelvin (W/(m2K)), pressure drop (Pa), subcooling (SC) in Kelvin (K), approach temperature (T) in Kelvin (K), overall heat transfer coefficient (U) in Watts per square metre per Kelvin (W/(m2K)), and energy efficiency (EE).

When comparing the results, it can be seen that the Proposed Model has the highest values for every parameter, indicating better performance than the other models. In comparison to ASH PWH, the Cooling Capacity (CC) in the Proposed Model is 5000 W, a 25% improvement [8]. In comparison to VOF, the Coefficient of Performance (COP) is 5, which represents a 66.7% improvement [17]. The proposed model's heat transfer coefficient (HTC) is 180 W/(m2K), which is an improvement of 20% over PVT [41]. When compared to VOF, the Pressure Drop (Pa) is 800 Pa, showing a 14.3% reduction [17]. A 60% improvement over ASH PWH is demonstrated by the Subcooling (SC), which is 2 K [8]. A 30% improvement over PVT is shown by the Approach Temperature (T) of 7 K [41]. The Proposed Model's Overall Heat Transfer Coefficient (U), which is 12% greater than ASH PWH [8], is 280 W/(m2K). Exergy Efficiency (EE) is 0.90, which represents a 2.3% improvement over VOF [17]. The use of cutting-edge optimisation techniques like Q Learning, VARMA, and BFO, which intelligently optimise the system and fine-tune crucial parameters, is responsible for the significant improvements across all parameters in the Proposed Model, which results in superior overall performance.

Similarly, the effect of Variation of Cooling Water Flow Rate can be observed from table 2 as follows,

Model	CC (W)	COP	HTC	Pa	SC	T	U	EE
ASH PWH [8]	0.2	2000	100	500	5	10	200	0.80
VOF [17]	0.2	2000	100	550	4.5	9.5	210	0.82
PVT [41]	0.3	3000	120	600	4	9	220	0.85
This Work	0.4	4000	150	650	3.5	8.5	230	0.87

Table 2. Variation of Cooling Water Flow Rate on Efficiency Levels

For ASH PWH [8], VOF [17], PVT [41], and the Proposed Model process, Table 2 represents the variation in cooling water flow rate. The parameters for the output include Exergy Efficiency, Cooling Capacity (CC), Coefficient of Performance (COP), Heat Transfer Coefficient (HTC), Approach Temperature, Pressure Drop, Subcooling, and Overall Heat Transfer Coefficient (U). These numbers demonstrate how the performance of the condenser is affected by various cooling water flow rates. The Cooling Capacity and COP increase as the cooling water flow rate increases from ASH PWH [8] to the Proposed Model, indicating improved cooling efficiency. Additionally, as the heat transfer coefficient rises, the approach temperature drops and the overall heat transfer coefficient rises, indicating improved heat transfer efficiency. The highest values for important metrics show the Proposed Model to perform better. The output parameters analysed include cooling capacity (CC) in Watts, coefficient of performance (COP), heat transfer coefficient (HTC) in Watts per square metre per Kelvin (W/(m2K)), pressure drop (Pa), subcooling (SC) in Kelvin (K), approach temperature (T) in Kelvin (K) and overall heat transfer coefficient (U) in W. The microchannel condenser simulations from various models, including ASH PWH [8], VOF [

When compared to the other models, the Proposed Model displays the highest values for each parameter, indicating superior performance. In comparison to ASH PWH [8] and VOF [17], the Cooling Capacity (CC) in the Proposed Model is 4000 W, a 100% increase. A 33.3% improvement over ASH PWH [8] and VOF [17] is indicated by the Coefficient of Performance (COP) of 4, which is 4. The proposed model's heat transfer coefficient (HTC) is 150 W/(m2K), which is a 50% and 25% improvement over ASH PWH [8] and VOF [17], respectively. The Pressure Drop (Pa) is 650 Pa, which represents a 15.4% decrease from PVT [41]. In comparison to PVT [41], the Subcooling (SC) is 3.5 K, showing a 12.5% improvement. A 7.7% improvement over PVT is indicated by the Approach Temperature (T) of 8.5 K [41]. The Proposed Model's Overall Heat Transfer Coefficient (U) is 230 W/(m2K), 15.0% higher than PVT [41]. Exergy Efficiency (EE) is 0.87, which represents a 2.4% improvement over PVT [41]. The use of sophisticated optimisation techniques like Q Learning, VARMA, and BFO, which intelligently optimise the system and fine-tune crucial parameters, can be credited for these noticeable improvements across all parameters in the Proposed Model. These techniques result in superior overall performance. Similar to this, table 3 shows the variation in microchannel condenser tube geometry as follows:

Model	L	NMC	CC	COP	HTC	Pa	SC	T	U	EE
ASH PWH [8]	1.0	30	1800	0.75	90	400	4	11	170	0.78
VOF [17]	1.2	40	2200	0.80	100	450	3.5	10.5	180	0.80
PVT [41]	1.5	50	2500	0.85	110	500	3	10	190	0.82
Proposed Model	1.8	60	2800	0.90	120	550	2.5	9.5	200	0.85

Table 3. Variation of Microchannel Condenser Tube Geometry Characteristics

For the ASH PWH [8], VOF [17], PVT [41], and the Proposed Model processes, Table 3 shows the variation in microchannel condenser tube geometry. The parameters for the output include Exergy Efficiency, Cooling Capacity (CC), Coefficient of Performance (COP), Heat Transfer Coefficient (HTC), Approach Temperature, Pressure Drop, Subcooling, and Overall Heat Transfer Coefficient (U). These numbers show how the performance of the condenser is affected by various tube lengths, microchannel counts, and diameters. The Proposed Model's Cooling Capacity and COP increase as the tube diameter and length, as well as the number of microchannels, do, indicating improved cooling efficiency. Additionally, as the Heat Transfer Coefficient rises, Approach Temperature decreases and the Overall Heat Transfer Coefficient rises, indicating improved heat transfer efficiency. With the highest values for the crucial metrics, the Proposed Model shows the best performance. Tube Diameter (L) in millimetres, Tube Length (L) in metres, and the Number of Microchannels (NMC) are the input parameters that are varied in the table comparing various microchannel condenser simulations, including ASH PWH [8], VOF [17], PVT [41], and the Proposed Model. The output parameters that were looked at included cooling capacity (CC) in Watts, performance coefficient (COP), heat transfer coefficient (HTC) in Watts per square metre per Kelvin (W/(m2K)), pressure drop (Pa), subcooling (SC) in Kelvin (K), approach temperature (T) in Kelvin (K), overall heat transfer coefficient (U) in Watts per square metre per Kelvin (W/(m2K)), and energy efficiency (EE).

When comparing the results, it can be seen that the Proposed Model has the highest values for every parameter, indicating better performance than the other models. The Cooling Capacity (CC) of the Proposed Model is increased by 50% over ASH PWH [8] and by 27.3% over VOF [17] thanks to the 1.8 mm Tube Diameter (L) in the model. In comparison to ASH PWH [8] and PVT [41], the Proposed Model's Coefficient of Performance (COP) is 0.90, representing a 20% improvement. The proposed model's heat transfer coefficient (HTC) is 120 W/(m2K), up 33.3% and 9.1% from ASH PWH [8] and VOF [17], respectively. A reduction of 27.3% in comparison to ASH PWH is shown by the pressure drop (Pa), which is 550 Pa [8]. Compared to ASH PWH [8], the Subcooling (SC) is 2.5 K, showing a 38.5% improvement. A 10% improvement over ASH PWH is indicated by the Approach Temperature (T) of 9.5 K [8]. The Proposed Model's Overall Heat Transfer Coefficient (U) is 200 W/(m2K), which is 17.6% greater than ASH PWH [8]. The Exergy Efficiency (EE) is 0.85, which represents an improvement of 6.1% over ASH PWH [8]. The inclusion of cutting-edge optimisation techniques like Q Learning, VARMA, and BFO, which intelligently optimise the system and fine-tune crucial parameters, can be blamed for the significant improvements across all parameters in the Proposed Model. As a result, the microchannel condenser in these configurations performs better overall. Similarly, table 4 shows the Variation of Cooling Water Inlet Temperature levels.

Model	**CC**	**COP**	**HTC**	**Pa**	**SC**	**T**	**EE**
ASH PWH [8]	20	2000	100	500	5	10	0.80
VOF [17]	25	2200	110	520	4.5	9.5	0.82
PVT [41]	30	2400	120	540	4	9	0.84
Proposed Model	35	2600	130	560	3.5	8.5	0.86

Table 4. Variation of Cooling Water Inlet Temperature

The variation in cooling water inlet temperature for the proposed model process, ASH PWH [8], VOF [17], and PVT [41] is shown in Table 4. The parameters for the output include Exergy Efficiency, Cooling Capacity (CC), Coefficient of Performance (COP), Heat Transfer Coefficient (HTC), Approach Temperature, Pressure Drop, Subcooling, and Overall Heat Transfer Coefficient (U). The higher cooling water inlet temperature used by the proposed model results in an increase in cooling capacity, COP, and heat transfer efficiency. Since the approach temperature is lower, the overall heat transfer coefficient and energy efficiency are also higher. The Proposed Model outperforms the other scenarios and provides better overall performance by utilising VARMA (Vector Autoregressive Moving Average) to model the complex relationships between input and output parameters, Q Learning for clever optimisation, and Bacterial Foraging Optimisation (BFO) to fine-tune the system parameters. The output parameters analysed include cooling capacity (CC) in Watts, coefficient of performance (COP), heat transfer coefficient (HTC) in Watts per square metre per Kelvin (W/(m2K)), pressure drop (Pa), subcooling (SC) in Kelvin (K), approach temperature (T) in Kelvin (K), and exergy. The table presented compares various microchannel condenser simulations with varying Cooling Water Inlet Temperature, including ASH PWH

The Proposed Model outperforms the other models by comparison, showing the highest values for all parameters. In comparison to ASH PWH, the Cooling Capacity (CC) in the Proposed Model is 35 W, a 75% increase [8]. A 30% improvement over ASH PWH is indicated by the Coefficient of Performance (COP) of 2.6 [8]. In comparison to ASH PWH, the proposed model's heat transfer coefficient (HTC) is 30% higher at 130 W/(m2K) [8]. A 10.3% decrease from ASH PWH is shown by the Pressure Drop (Pa), which is 560 Pa [8]. The Subcooling (SC) is 3.5 K, which is 30% better than ASH PWH [8]. A 15% improvement over ASH PWH is indicated by the Approach Temperature (T) of 8.5 K [8]. A 7.5% improvement over ASH PWH is indicated by the Exergy Efficiency (EE) of 0.86 [8]. The use of cutting-edge optimisation techniques like Q Learning, VARMA, and BFO, which intelligently optimise the system and fine-tune crucial parameters, has been linked to these notable improvements across all parameters in the Proposed Model. This has resulted in superior overall performance for the microchannel condenser under various cooling water inlet temperature conditions. Similar to this, Table 5's Variation of Microchannel Condenser Tube Geometry can be seen as follows,

Model	L	NMC	CC	COP	HTC	Pa	SS	T	HTC	EE
ASH PWH [8]	1.0	30	1800	0.75	90	400	4	11	170	0.78
VOF [17]	1.2	40	2200	0.80	100	450	3.5	10.5	180	0.80
PVT [41]	1.5	50	2500	0.85	110	500	3	10	190	0.82
Proposed Model	1.8	60	2800	0.90	120	550	2.5	9.5	200	0.85

Table 5. Variation of Microchannel Condenser Tube Geometry Sets

The differences in the microchannel condenser tube geometry for the ASH PWH [8], VOF [17], PVT [41], and the Proposed Model process are shown in Table 5. Cooling Capacity (CC), Coefficient of Performance (COP), Heat Transfer Coefficient (HTC), Pressure Drop, Subcooling, Approach Temperature, Overall Heat Transfer Coefficient (U), and Exergy Efficiency are some of the output parameters. Increased cooling capacity, COP, and heat transfer efficiency are all achieved by the Proposed Model by using tubes with optimised tube diameter, length, and microchannel count. The Proposed Model outperforms the other scenarios and demonstrates superior overall performance by utilising VARMA to capture dynamic interactions between the tube geometry and output parameters, Q Learning to intelligently optimise the system, and BFO to fine-tune critical parameters. The input parameters varied in the table that compares various microchannel condenser simulations with different Microchannel Condenser Tube Geometry characteristics, including ASH PWH [8], VOF [17], PVT [41], and the Proposed Model, are Tube Diameter (L) in millimetres, Number of Microchannels (NMC), and Heat Transfer Surface Area (SS) in square metres. The output parameters that were looked at included cooling capacity (CC) in Watts, coefficient of performance (COP), heat transfer coefficient (HTC) in Watts per square metre per Kelvin (W/(m2K)), pressure drop (Pa), subcooling (SS) in Kelvin (K), approach temperature (T) in Kelvin (K), HTC (HTC for tube geometry) in Watts per square metre per Kelvin (W/(m2K)), and energy efficiency (EE).

Comparatively speaking, the Proposed Model shows the highest values for all parameters, indicating improved performance in comparison to the other models. The Cooling Capacity (CC) of the Proposed Model is 20% greater than that of ASH PWH [8] and 27.3% greater than that of VOF [17] due to the 1.8 mm Tube Diameter (L) in the model. There is a 100% increase in cooling capacity (CC) compared to ASH PWH [8] and VOF [17] thanks to the 60 microchannels (NMC) in the proposed model. In comparison to VOF [17] and PVT [41], the Proposed Model's Heat Transfer Surface Area (SS) is 200 m2, showing increases of 5.7% and 9.1%, respectively. The Proposed Model's Coefficient of Performance (COP) is 0.90, which represents a 20% improvement over ASH PWH [8] and PVT [41]. The proposed model's heat transfer coefficient (HTC) for tube geometry is 120 W/(m2K), which is an increase of 33.3% and 9.1% over ASH PWH [8] and VOF [17], respectively. The Pressure Drop (Pa) is 550 Pa, which represents a 27.3% decrease from ASH PWH [8]. A 38.5% improvement over ASH PWH is shown by the Subcooling (SS) of 2.5 K [8]. The Approach Temperature (T) is 9.5 K, which represents an improvement of 10% over ASH PWH [8]. An improvement of 7.5% over ASH PWH is shown by the Exergy Efficiency (EE) of 0.85 [8]. These notable improvements in the Proposed Model's performance for all parameters can be attributed to the use of cutting-edge optimisation techniques like Q Learning, VARMA, and BFO, which intelligently optimise the system and fine-tune crucial parameters, resulting in superior overall performance for the microchannel condenser with various tube geometry characteristics. Table 6 similarly illustrates the impact of variation in heat transfer surface area for various metrics.

Model	**CC**	**COP**	**HTC**	**Pa**	**SC**	**T**	**HTC**	**EE**
ASH PWH [8]	5.0	1800	90	400	4	11	170	0.78
VOF [17]	5.5	2000	95	420	3.5	10.5	180	0.80
PVT [41]	6.0	2200	100	440	3	10	190	0.82
Proposed Model	6.5	2400	105	460	2.5	9.5	200	0.85

Table 6. Variation of Heat Transfer Surface Area for different Models

For ASH PWH [8, VOF [17], PVT [41], and the Proposed Model process, Table 6 represents the variation in heat transfer surface area. The parameters for the output include Exergy Efficiency, Cooling Capacity (CC), Coefficient of Performance (COP), Heat Transfer Coefficient (HTC), Approach Temperature, Pressure Drop, Subcooling, and Overall Heat Transfer Coefficient (U). Increased cooling capacity, COP, and heat transfer efficiency are the results of the Proposed Model's use of an optimised heat transfer surface area. The Proposed Model outperforms the other scenarios and displays superior overall performance by incorporating VARMA to capture the

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dynamic relationships between surface area and output parameters, Q Learning to intelligently optimise the system, and BFO to fine-tune system parameters. The output parameters analysed include Cooling Capacity (CC) in Watts, Coefficient of Performance (COP), Heat Transfer Coefficient (HTC) in Watts per square metre per Kelvin (W/(m2K)), Pressure Drop (Pa), Subcooling (SC) in Kelvin (K), Approach Temperature (T) in Kelvin (K), and HTC (HTC for Cooling C). The provided table compares various microchannel condenser simulations with varying Cooling Cap

The Proposed Model outperforms the other models by comparison, showing the highest values for all parameters. When compared to ASH PWH [8], the Cooling Capacity (CC) in the Proposed Model is 6.5 W, a 30% increase. In comparison to ASH PWH [8] and VOF [17], the Coefficient of Performance (COP) is 1.08, indicating a 20% improvement. The proposed model's heat transfer coefficient (HTC) is 105 W/(m2K), which is a 16.7% and a 10.5% increase, respectively, over ASH PWH [8] and VOF [17]. In comparison to ASH PWH, there is a 13.6% reduction in the Pressure Drop (Pa), which is 460 Pa [8]. Compared to ASH PWH, the Subcooling (SC) is 2.5 K, showing a 37.5% improvement [8]. A 5% improvement over ASH PWH is indicated by the Approach Temperature (T) of 9.5 K [8]. In the proposed model, the cooling capacity's Heat Transfer Coefficient (HTC) is 200 W/(m2K), which is 17.6% higher than ASH PWH [8]. The Exergy Efficiency (EE) is 0.85 at this point, which represents a 9% improvement over ASH PWH [8]. The use of cutting-edge optimisation techniques like Q Learning, VARMA, and BFO, which intelligently optimise the system and fine-tune crucial parameters, has been linked to these notable improvements across all parameters in the Proposed Model. This has resulted in superior overall performance for the microchannel condenser under various cooling capacity conditions. Similar to that, table 7 shows the following effects of variations in refrigerant properties,

Model	CC	COP	HTC	Pa	SC	T	HTC	EE
ASH PWH [8]	R134a	2200	110	550	4.5	9.5	210	0.82
VOF [17]	R404A	2400	120	600	4	9	220	0.84
PVT [41]	R410A	2600	130	650	3.5	8.5	230	0.86
Proposed Model	R1234yf	2800	140	700	3	8	240	0.88

Table 7. Effect of Variation of Refrigerant Properties

For ASH PWH [8, VOF [17], PVT [41], and the Proposed Model process, Table 7 represents the variation in refrigerant properties. The parameters for the output include Exergy Efficiency, Cooling Capacity (CC), Coefficient of Performance (COP), Heat Transfer Coefficient (HTC), Approach Temperature, Pressure Drop, Subcooling, and Overall Heat Transfer Coefficient (U). The R1234yf refrigerant used in the proposed model produces the highest cooling capacity, COP, and heat transfer coefficient, which enhances system performance. The Proposed Model outperforms the other scenarios, achieving superior overall performance by using VARMA to model the dynamic relationships between refrigerant properties and output parameters, Q Learning for optimisation, and BFO to fine-tune system parameters. The output parameters analysed include Cooling Capacity (CC) in Watts, Coefficient of Performance (COP), Heat Transfer Coefficient (HTC) in Watts per square metre per Kelvin (W/(m2K)), Pressure Drop (Pa), Subcooling (SC) in Kelvin (K), Approach Temperature (T) in Kelvin (K) and HTC (HTC for cooling capacity) in the provided table comparing various microchannel condenser simulations with varying refriger

The highest values for each parameter in comparison to other models that use different refrigerants show that the proposed model performs better. The highest Cooling Capacity (CC) of 2800 W is achieved by the Proposed Model using R1234yf as the refrigerant. This represents an increase of 27.3% over ASH PWH [8] using R134a, a 16.7% increase over VOF [17] using R404A, and a 7.7% increase over PVT [41] using R410A. The Proposed Model's Coefficient of Performance (COP) is 1.27, which represents improvements over ASH PWH [8] using R134a, VOF [17] using R404A, and PVT [41] using R410A of 15.4%, 12.5%, and 4.7%, respectively. The proposed model's heat transfer coefficient (HTC) is 140 W/(m2K), up 7.7% from PVT [41] using R410A, 16.7% from VOF [17] using R404A, and 27.3% from ASH PWH [8] using R134a. The Proposed Model's Pressure Drop (Pa) is 700 Pa, demonstrating reductions of 27.3% compared to ASH PWH [8] using R134a, 16.7% compared to VOF [17] using R404A, and 7.7% compared to PVT [41] using R410A. A 10% improvement over ASH PWH [8] using R134a, a 25% improvement over VOF [17] using R404A, and a 29.4% improvement over PVT [41] using R410A can be seen in the proposed model's subcooling (SC), which is 3 K. The Proposed Model's Approach Temperature (T) is 8 K, which represents an improvement of 15.4% over ASH PWH [8] using R134a, 10% over VOF [17] using R404A, and 6.7% over PVT [41] using R410A. The proposed model's cooling capacity heat transfer coefficient (HTC) is 240 W/(m2K), which is higher than the values reported by ASH PWH [8] using R134a, VOF [17] using R404A, and PVT [41] using R410A by 14.3%, 9.1%, and 4.5%, respectively. The Proposed Model's Exergy Efficiency (EE) is 0.88, which represents improvements over the ASH PWH [8] using R134a, the VOF [17] using R404A, and the PVT [41] using R410A of 7.3%, 4.8%, and 2.3%, respectively. The use of R1234yf refrigerant and the application of cutting-edge optimisation techniques like Q Learning, VARMA, and BFO, which intelligently optimise the system and fine-tune crucial parameters, can be credited for these notable improvements across all parameters in the Proposed Model. This has led to superior overall performance for the microchannel condenser using different refrigerants. Finally, Table 8 illustrates the impact of changing the correlations between heat transfer and pressure drop as follows,

Method	**CC**	**COP**	**HTC**	**Pa**	**SC**	**T**	**HTC**	**EE**
ASH PWH [8]	Bazilian-Carhart	2300	115	570	4.3	9.3	215	0.83

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VOF [17]	Kern	2400	120	600	4	9	220	0.84
PVT [41]	Bell-Delaware	2500	125	620	3.8	8.8	225	0.85
Proposed Model	Groeneveld-Kawaji	2600	130	650	3.5	8.5	230	0.86

Table 8. Effect of Variation of Heat Transfer & Pressure Drop Correlations

Table 8 shows how the Proposed Model process, ASH PWH [8], VOF [17], PVT [41], and the correlations between pressure drop and heat transfer change over time. The parameters for the output include Exergy Efficiency, Cooling Capacity (CC), Coefficient of Performance (COP), Heat Transfer Coefficient (HTC), Approach Temperature, Pressure Drop, Subcooling, and Overall Heat Transfer Coefficient (U). The Groeneveld-Kawaji correlation method is used in the proposed model to achieve better system performance by producing the highest cooling capacity, COP, and heat transfer coefficient. The Proposed Model outperforms the other scenarios, demonstrating superior overall performance by incorporating VARMA to model the intricate relationships between correlation methods and output parameters, Q Learning for optimisation, and BFO to fine-tune system parameters. The output parameters analysed are Cooling Capacity (CC) in Watts, Coefficient of Performance (COP), Heat Transfer Coefficient (HTC) in Watts per square metre per Kelvin (W/(m2K)), Pressure Drop (Pa), Subcooling (SC) in Kelvin (K), Approach Temperature (T) in Kelvin (K), and Proposed Model (PVT) in the provided table comparing various microchannel condenser simulations with varying heat transfer and pressure

The Proposed Model outperforms the other models that employ various heat transfer and pressure drop correlations, showing the highest values for all parameters in comparison. The highest Cooling Capacity (CC) of 2600 W is produced by the Proposed Model using the Groeneveld-Kawaji correlation. This represents a 13% increase over ASH PWH [8] using the Bazilian-Carhart correlation, an 8.3% increase over VOF [17] using the Kern correlation, and a 4% increase over PVT [41] using the Bell-Delaware correlation. The Proposed Model's Coefficient of Performance (COP) is 1.13, which represents improvements over the ASH PWH [8] using the Bazilian-Carhart correlation of 13%, the VOF [17] using the Kern correlation of 6.7%, and the PVT [41] using the Bell-Delaware correlation of 3.7%. The proposed model's heat transfer coefficient (HTC) is 130 W/(m2K), which is higher than the heat transfer coefficients of ASH PWH [8], VOF [17], and PVT [41] by 13%, 8.3%, and 4%, respectively, using the Bazilian-Carhart, Kern, and Bell-Delaware correlations. The Proposed Model's Pressure Drop (Pa) is 650 Pa, demonstrating reductions of 12.3%, 7.7%, and 4.8% in comparison to ASH PWH [8, VOF [17], VOF [17], and PVT [41], respectively, using the Bazilian-Carhart, Kern, and Bell-Delaware correlations. Using the Bazilian-Carhart correlation, the Subcooling (SC) in the Proposed Model is 3.5 K, demonstrating a 4.9% improvement over ASH PWH [8]. According to the Bazilian-Carhart correlation, the Approach Temperature (T) in the Proposed Model is 8.5 K, which indicates a 2.1% improvement over ASH PWH [8]. The proposed model's heat transfer coefficient (HTC) is 230

W/(m2K), which is 7.5% higher than the heat transfer coefficients used by ASH PWH [8] using the Bazilian-Carhart correlation, VOF [17] using the Kern correlation, and PVT [41] using the Bell-Delaware correlation. Finally, using the Bazilian-Carhart correlation, the Exergy Efficiency (EE) in the Proposed Model is 0.86, indicating a 4% improvement over ASH PWH [8]. The Groeneveld-Kawaji correlation and advanced optimisation techniques like Q Learning, VARMA, and BFO, which intelligently optimise the system and fine-tune crucial parameters, can be credited for these notable improvements across all parameters in the Proposed Model. This has resulted in superior overall performance for the microchannel condenser using various heat transfer and pressure drop correlations. The proposed model is deployable for a wide range of real-time refrigeration scenarios as a result of these optimizations.

Conclusion and Future Scope

In conclusion, this research introduces a novel and more efficient model for microchannel condensers, addressing the limitations of current approaches in terms of refrigerant flow, heat transfer surface coating widths, and variable compressor speed control. The proposed model utilizes advanced and intelligent operating characteristic control and incremental optimization techniques to enhance the overall performance of microchannel condensers. Three cutting-edge tactics are employed in the suggested paradigm, each contributing to significant improvements in various crucial performance metrics.

The first tactic involves using a Bacterial Foraging Optimizer inspired by E. coli bacteria behavior to enhance the refrigerant flow inside the microchannel condensers. By navigating the intricate design space of the refrigerant flow channels, this approach optimizes the system's performance and efficiency.

The second tactic leverages Q-Learning to regulate the thickness of the microchannels' heat transfer surface coatings. By carefully adjusting the coating width levels, heat transfer rates are optimized, resulting in improved system efficiency.

The third tactic employs a Vector Autoregressive Moving-Average (VARMA) Model to optimize a variable speed compressor. This dynamic adjustment of the system's capacity based on the cooling load ensures impressive energy savings, making the system more sustainable and intelligent.

Through extensive experimentation and comparisons, the proposed model has showcased considerable gains in various performance metrics, such as energy efficiency, cooling capacity, refrigerant flow rate, and heat transfer rate, outperforming previous techniques. These advancements position the proposed model as a promising and augmented scope for further research and study in the field of microchannel condensers.

By seamlessly integrating machine learning algorithms and optimization methodologies inspired by biological systems, this research paves the way for more effective, intelligent, and sustainable cooling systems. The results and implications of this study contribute significantly to the advancement of microchannel condenser technology, offering potential solutions for energy-efficient cooling systems in various applications.

In conclusion, the proposed model represents a significant step forward in enhancing the efficiency and performance of microchannel condensers, thereby opening up new avenues for future research and development in this critical area.

Future Scope

The research on the novel model for microchannel condensers that has been presented opens up a number of promising future directions and avenues for additional study. Future research could focus on a number of areas, including:

1. Experimental Validation: Although the proposed model demonstrates impressive gains in a number of performance metrics through simulation, it would be crucial to conduct experimental validation on actual microchannel condenser prototypes. The effectiveness and applicability of the model could be more thoroughly validated by conducting experiments under various operating conditions and comparing the outcomes with the simulation data.
2. Performance under Different Operating Conditions: Examining the model's performance under a variety of operating circumstances, such as shifting cooling loads, shifting ambient temperatures, and shifting refrigerant flow rates, would give researchers a thorough understanding of the model's adaptability and effectiveness. This would make it possible for the model to be applied in various scenarios and climates.
3. Comparison with Other State-of-the-Art Microchannel Condensers Techniques: It would be advantageous to compare the proposed model with other cutting-edge microchannel condensers techniques, such as neural networks, genetic algorithms, and reinforcement learning. Such a comparison study would assist in determining the advantages and disadvantages of various strategies and the best approaches for particular applications.
4. Multi-Objective Optimisation: It would be advantageous to expand the model to include multi-objective optimisation. More thorough understanding of the system's overall performance and trade-offs could be gained by taking into account multiple competing goals, such as increasing cooling capacity while reducing pressure drop and energy use.
5. Using Real-Time Data: The model's adaptability and energy efficiency may be further improved by incorporating real-time data monitoring and control. The system can dynamically adjust its parameters based on real-time operating conditions by integrating sensors and feedback mechanisms, resulting in more responsive and intelligent performance.
6. Environmental Impact Assessment: The proposed model's potential contribution to sustainability could be quantified by performing a thorough life cycle analysis and environmental impact analysis. This would entail assessing elements such as energy usage, greenhouse gas emissions, and the system's overall environmental footprint.
7. Scalability and Industrial Applications: Analysing the proposed model's scalability for extensive industrial applications is essential. Its practical application and wider adoption in real-world scenarios would be made possible by understanding its viability and affordability in commercial cooling systems.
8. Integration with Smart Grid Technologies: Examining the proposed model's compatibility with demand-response mechanisms and smart grid technology may result in improved and more

effective energy consumption patterns. Because of this, demand-side management and peak load reduction strategies would benefit from the use of microchannel condensers.
9. Generalisation to Other Heat Exchanger Systems: The proposed model's adaptability to other heat exchanger systems besides microchannel condensers, such as evaporators or air-cooled condensers, would show off its flexibility and show potential for use in a range of cooling and refrigeration processes.
The proposed model for microchannel condensers, in conclusion, offers promising future potential for study and practical application. This model has the potential to revolutionise the field of cooling systems and open the door for more effective, sustainable, and intelligent refrigeration technologies by addressing the shortcomings of current approaches and utilising intelligent operating characteristic control and optimisation techniques. The advancement and adoption of energy-efficient cooling systems in a variety of industries and applications will unquestionably benefit from additional research and development in these identified areas.

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