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Passive Heat Transfer Augmentation in Low-Temperature Organic Rankine Cycle Systems Using Twisted Tape Inserts: Impact on Working Fluid Flow Behavior and Power Output

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Abstract

INTRODUCTION: The Organic Rankine Cycle (ORC) systems are considered to be the best for low-grade heat recovery. However, limited studies have integrated passive heat-transfer enhancement, deep learning prediction, and ORC optimisation within a unified framework under varying operating conditions.
OBJECTIVES: Here, an integrated framework based on Deep Neurone Networks (DNNs) is proposed which includes prediction and optimization to model the non-linear relationships with great precision and thereby improve the entire ORC system performance.
METHODS: The DNN was trained on the simulation data generated from different combinations of twist ratios, heat inputs, flow rates, and thermodynamic conditions.
RESULTS: The DNNs predicted key thermal-hydraulic and thermodynamic performance indicators with high accuracy under varying ORC operating conditions. This model exhibited excellent predictive capability as indicated by R^2 values surpassing 0.98 for all the outputs, and very low errors like MAE = 0.0027 and RMSE = 0.0036 for the thermal performance factor prediction.
CONCLUSION: Further optimization revealed major improvements, resulting in Nusselt number of 769.108, thermal performance factor of 1.6452, and net power output of 4.672 kW under the best conditions. Additionally, thermal and exergy efficiencies grew to 6.961% and 25.160% respectively indicating that heat transfer and energy utilization have become more effective. In summary, the suggested framework is a reliable and precise tool for assessing and optimizing ORC systems, thereby providing better insights into performance for thermal system design and operational decision-making.

Keywords: Organic Rankine Cycle, Twisted Tape Inserts, Deep Learning, Heat Transfer Enhancement, System Optimisation

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1. Introduction

The technology of low-temperature ORC has gained growing acceptance for waste heat recovery from low-grade heat sources such as geothermal energy and industrial processes [1]. High performance is difficult to achieve because of the limitations that these systems impose on heat transfer

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efficiency and pressure loss through the evaporator [2]. Among several passive heat transfer augmentation techniques, the twisted tape inserts have been the most effective ones for increasing the heat transfer coefficient and improving the thermal characteristics of the exchanger [3]. These inserts create turbulence in the flow, which results in a substantial increase in heat transfer; however, an increase in pressure drop occurs simultaneously, which ultimately lowers the efficiency of the system [4]. It uses deep learning (DL) techniques to predict and optimise ORC system behaviour while balancing heat-transfer enhancement and pressure-drop penalties for improved low-temperature ORC performance [5].

The various contemporary methods, including empirical correlations, CFD simulations, and thermodynamic modelling, have all contributed to the enhancement of ORC systems' performance [6]. Empirical models like those based on friction factor models for pressure drop and Nusselt number correlations for heat transfer might provide quick approximations, but they often fail in a wide range of operating conditions [7]. CFD simulations, on the other hand, have been adopted to gain a thorough understanding of the fluid flow and heat transport, even though they are very expensive and time-consuming [8]. Thermodynamic models usually apply 0D or 1D approaches, and these models are capable of providing a simple yet powerful tool to analyse ORC cycles; however, they tend to ignore the complicated flow characteristics and non-linear interactions [9]. The limited studies have integrated passive heat-transfer enhancement, thermodynamic simulation, deep learning prediction, and optimisation within a unified ORC framework under varying operating conditions. [10].

The cons of these techniques are managed using the simultaneous strategy of a DNNs and an ORC (Organic Rankine Cycle) model developed with Simulink. The DNN provides a fast and accurate approach for predicting key performance indicators such as heat transfer coefficient, pressure drop, and net power output under varying operating conditions. This outstanding combination allows the alterations of the system settings, including the twist ratio and flow rate, to be done in real-time with the purpose of optimising the TPF and minimising the pressure drop simultaneously. The suggested solution not only enables the upgrading of ORC systems with twisted tape inserts to be more efficient, but also removes the limitations of high computation and less precise traditional approaches. This enhances the accuracy of prediction and improvement of the operational aspect.

The present research makes use of a novel technique that integrates a DNN with a Simulink-based ORC model to upgrade the performance of low-temperature ORC systems utilizing twisted tapes as inserts. The main aspect addressing the drawbacks of the common solutions is the usage of Deep Learning to predict in real-time and refine such performance indicators as the pressure drop and heat transfer coefficient. The proposed framework provides a computationally efficient approach for balancing heat-transfer enhancement and pressure-drop reduction to optimise ORC system performance under varying operating conditions.

1.1. Research Objectives

1. Develop an integrated framework to optimise low-temperature ORC system performance using twisted tape inserts by balancing heat transfer enhancement and pressure drop through Deep Learning techniques and simulation-based modelling.

2. Use simulation data generated from the ORC cycle model to train and validate the DNN model, thereby ensuring accurate prediction of key performance indicators such as heat transfer coefficient, pressure drop, and net power output.

3. Integrate the Simulink-based ORC model with the trained DNNs to predict and optimise process parameters such as twist ratio and flow rate for improved thermal performance and reduced pressure drop.

4. Optimization methods will be applied in the framework to improve total performance of the system by increasing TPF, while maintaining practical limits on pressure drop and operating temperature.

1.2. Research Organisation

The structure of this paper is as follows: The Introduction is presented in Section 1, which also describes the problem and the purpose of the research. Section 2 will provide a Literature Review, which will cover the current methods as well as their shortcomings. Section 3 gives the Problem Statement, which focuses on the necessity to optimise. Section 4 explains the Methodology, including the framework and methodology. The Results and Discussions of Section 5 compare performance of proposed framework with traditional methods. Lastly, Section 6 summarises the paper with a conclusion on the major findings and proposes research directions in the future.

2. Literature review

Studies of Parabolic Trough Collectors (PTCs) as an ORC system have concentrated on enhancing the thermal efficiency. Aquino-Santiago et al. [11] used a thermodynamic model to assess the thermal performance of concentrically annular receiver-based PTCs. Due to a lack of dynamic operational optimisation, this does not fully apply to other system designs, although the model has a superior heat transfer at lower flow rates. Simultaneously, Ma et al. [12] suggested using annular sector inserts (A-S-PTR) to improve heat transfer in Parabolic Trough Receivers (PTRs) and optimise the design parameters with the help of the NSGA-II. Their approach, however, does not allow for changing system parameters in real time with respect to different operating conditions. Daniarta et al. [13] developed a MATLAB model of TES-evaporator and TES-liquid heater pairs with a focus on thermal energy storage (TES) in ORC systems based on phase change materials (PCMs). This technique is not so flexible in optimizing the parameters of the system and it may also create more difficulties in the dynamic adjustment of the system to the new operating conditions.

Other works used the latent heat storage (LHS) that was incorporated in the ORC systems to examine solar thermal power generation. Dixit et al. [14] also used a mathematical methodology to compare various working fluids (WFs) and heat transfer fluids (HTFs), but not real-time optimisation across working conditions. In the same manner, Cavazzini et al. [15] evaluated the application of metal-organic heat carriers (MOHCs) as a means to improve the heat transfer in an ORC system, but the numerical model is confined by the fixed fluid ratios and the inability to optimise the factors. Syngounas et al. [16] investigated a pumpless Rankine cycle (PRC) with R245fa based on validated MATLAB simulation models, but they had not provided real-time adjustments for changing operating parameters. Although the research by Tauveron et al. [17] focused on the use of submerged evaporators to reclaim waste heat in nuclear reactors; its optimisation of the experimental system is not dynamic and cannot be adjusted to reflect changing working conditions.

Li et al. [18] compared the performance of various HTFs and WFs and suggested a combined system to be installed in data centres that incorporates solar collectors and the ORC systems. The study is not optimised for parameter changes in real time, limiting the flexibility of the study. Kumar et al. [19] provided a dynamic simulation of an ORC system with PCMs to store latent heat; however, they did not discuss optimisation of the system in real-time. Finally, Alkotami et al. [20] assessed a solar-powered ORC system with different designs and working fluids. The fact that they offer a very insightful analysis on thermodynamics, but which is also limited in its ability to adapt dynamically to varying operational conditions because of absence of real-time optimisation, is also a major weakness of the existing approaches. Existing CFD-based studies provide detailed flow and thermal analysis but involve high computational cost and simulation time. Thermodynamic models offer faster system-level analysis but often simplify complex flow behaviour. In contrast, machine-learning-based methods improve prediction capability, although their accuracy depends strongly on training data quality. Therefore, the proposed integrated framework combines thermodynamic simulation and deep learning to achieve improved prediction accuracy and computational efficiency for ORC optimisation.

3. Problem statement

Research that previously tackled the topic of using twisted tape inserts, including the studies of Ranjbar et al. [21] Karana et al. [22], and Qasemian et al. [23] conditions already existing knowledge, but comes along with numerous shortcomings. As a matter of fact, a lot of these experiments limit the validity of their findings by only looking at one aspect of the problem at a time, such as twist ratio, heat transfer, and pressure drop, and not taking into account the complex interactions of other operational factors. Given that conventional methods mainly depend on empirical correlations or labour-intensive and computationally expensive experimental setups, they are very hard to adapt for use in changing conditions. The recent research on effect of inserts and nanoparticles on heat transfer and pressure drop still does not consider the integration of optimisation techniques for the real-time adjustment of important parameters, which, in turn, restricts the aorta of ORC systems optimally. The significant progress reported in previous studies on ORC performance enhancement and heat-transfer augmentation techniques, several limitations remain. Existing experimental and CFD-based investigations provide accurate thermal and flow analyses but often require substantial computational resources and long execution times, limiting their suitability for rapid optimisation and real-time applications. Furthermore, many conventional thermodynamic models do not effectively capture the complex nonlinear relationships among operating parameters, heat-transfer characteristics, and system performance indicators. To address these limitations, this study proposes an integrated DNN-ORC framework that combines thermodynamic modelling, deep learning-based prediction, and optimisation. The proposed approach aims to achieve accurate performance prediction with significantly reduced computational effort while supporting efficient optimisation of low-temperature ORC systems employing twisted tape inserts.

The suggested approach integrates Deep Learning with a Simulink-based ORC model, thus defeating these drawbacks and permitting the real-time predictions and optimisation across various operating parameters. In contrast to the classical methods, it takes into account simultaneously the temperature, mass flow rate and twist ratio, which results in a more comprehensive and efficient optimisation process. With the help of a DNN, accurate and scalable predictions can be made without the computational burden of CFD simulations or testing methods. Moreover, the integration of optimisation algorithms with the Simulink model gives the framework a more realistic and powerful approach to the optimisation of ORC systems with twisted tape inserts. It is thus possible to change the essential parameters in real-time for the purpose of optimising thermal performance and lowering pressure drop. Conventional thermodynamic and CFD-based approaches can accurately evaluate ORC system performance; however, they often require considerable computational effort and are less suitable for rapid optimisation studies involving numerous operating conditions. Deep learning methods provide an effective alternative by learning complex nonlinear relationships between operating parameters and performance indicators from simulation data. Therefore, the proposed framework leverages the capabilities of Deep Neural Networks (DNNs) to accurately predict heat-transfer characteristics, pressure drop, and net power output with significantly reduced computational time. This integration enables efficient optimisation and rapid performance assessment of low-temperature ORC systems employing twisted tape inserts.

4. Proposed deep learning-based optimisation methodology for heat transfer augmentation in orc systems

Figure 1 shows the optimised method for the ORC system incorporating twisted tape inserts as a suggestion. Selecting a working fluid (R245fa) and producing reliable fluid property calculations using MATLAB's CoolProp are the first steps. The next step is the ORC cycle model (0D), consisting of an evaporator, a pump, a condenser, and an expander. This evaporator model is done through a 1D control-volume method along with twisted tape insert correlations for pressure drop and heat transport. A neural network is applied to predict significant parameters, and subsequently, random searching is performed to get the maximum power production and the highest efficiency. Lastly, the model is verified by using performance evaluation criteria, including thermal efficiency, friction factor, Nusselt number, and thermal performance factor.

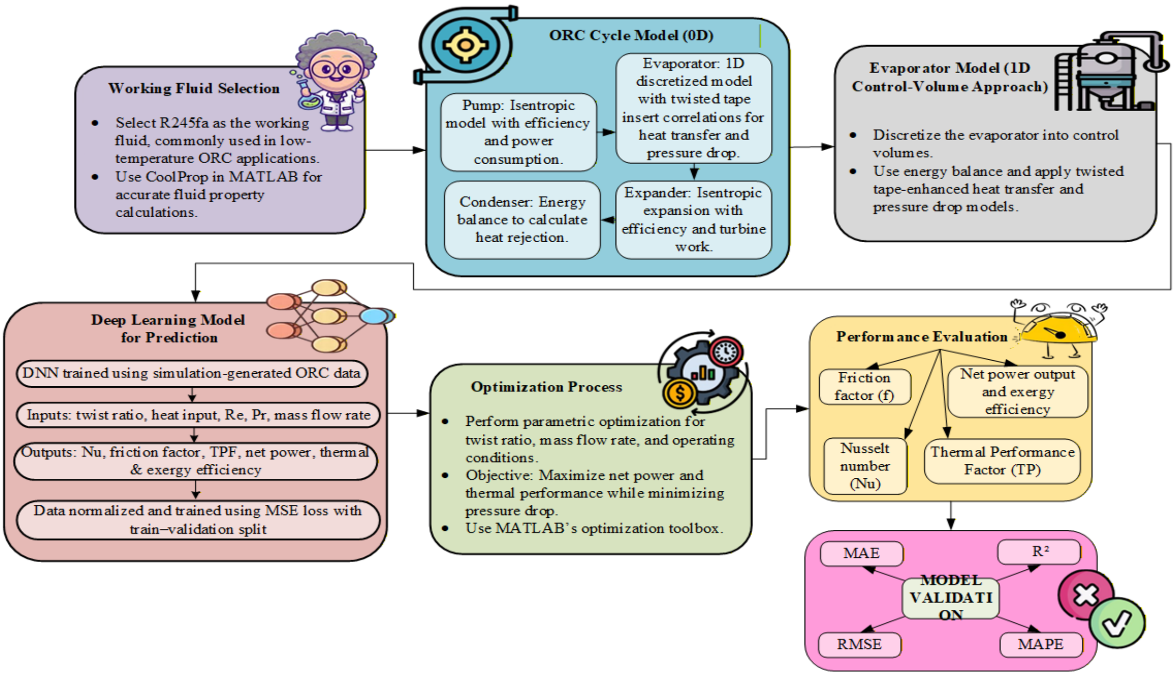


Figure 1. Methodological Framework for ORC Optimisation and Heat Transfer Augmentation

The suggested technique not only foresees but also enhances the performance of the system by employing a combination of a DNN and an ORC model designed in Simulink. In the course of training the DNN with ORC model's simulated data, significant operational factors such as temperature, flow rate, and twisting ratio are taken into account. The performance of the system is determined through application of main indicators such as pressure drop and heat transfer coefficient, which are affected by the twisted tape inserts. The framework, by means of applying real-time predictions and optimisation to pressure loss reduction and thermal performance improvement of the ORC system, presents a less costly and more efficient method in terms of computing for the enhancement of ORC cycle operations.

Step 1: Develop 0D thermodynamic ORC model to evaluate cycle performance under different operating conditions.

Step 2: Develop 1D evaporator model to analyse heat transfer and pressure drop characteristics with twisted tape inserts.

Step 3: Generate simulation dataset from ORC and evaporator models.

Step 4: Train Deep Neural Network (DNN) using simulation data for performance prediction.

Step 5: Integrate the trained DNN with the Simulink-based ORC model for real-time prediction.

Step 6: Apply optimisation to improve the thermal performance factor while limiting pressure drop.

4.1. Working Fluid Selection

In ORC systems, choice of working fluid is a decisive factor since it affects the performance, efficiency, and operating range of system directly. The working fluid must have a low boiling point in the case of low-temperature ORC applications so that it can extract heat efficiently from the lower temperature heat sources, like waste heat recovery or geothermal energy, etc.

The study opts for R245fa (1,1,1,3,3-Pentafluoropropane) as the working fluid owing to its good properties in low-temperature applications. The working fluid R245fa is a low-boiling organic substance that at 1 atm pressure has a boiling point of 15.3°C, which is thus appropriate for processes with a heat source temperature up to around 150°C and down to 80°C. Its low GWP (Global Warming Potential) and non-flammability characteristics make the fluid even more suitable for ORC systems, particularly in the case of industrial and geothermal applications, where safety and environmental factors are of prime importance.

Thermodynamic Properties of R245fa

By employing R245fa in either a sub- or transcritical ORC cycle, it will best fit in the systems with moderate-to-low-temperature heat sources. Thermodynamic parameters of R245fa are determined using MATLAB along with the software CoolProp so that heat transport and pressure drop within the ORC cycle can be precisely described.

CoolProp is an open-source database and library of thermophysical properties that grants the user accurate calculation of fluid properties. It calculates major thermodynamic values of R245fa at various pressures and temperatures such as saturation temperature, specific heat, entropy, and enthalpy among others.

Thermodynamic Relations:

1. **Enthalpy (h)**: This is used to track the energy added to working fluid during heat absorption process in evaporator.

2. **Entropy (s)**: This helps in analysing exergy efficiency of cycle and the irreversibility of heat transfer processes.

3. **Saturation Temperature and Pressure:** They are necessary for discerning R245fa's phase change behavior in the ORC cycle's evaporator and condenser areas. The temperature and pressure at which working fluid changes its state from liquid to vapor have a great influence on the system's thermal efficiency and performance as a whole.

CoolProp Integration in MATLAB:

For modeling the thermodynamic behavior of R245fa in MATLAB, the CoolProp library is invoked through MATLAB's CoolProp interface. This interface makes it possible to calculate thermodynamic properties at different operating conditions without any interruptions. As an example, the enthalpy of working fluid can be obtained at a specified temperature and pressure using subsequent MATLAB command shown as Eqn 1:

h = CoolProp.PropsSI('H', 'T', temperature, 'P', pressure, 'R245fa'); (1)

Where:
T represents the working fluid temperature measured in Kelvin (K), P denotes the operating pressure measured in Pascals (Pa), and h represents the specific enthalpy of the working fluid measured in Joules per kilogram (J/kg). These thermodynamic variables are used to calculate the fluid properties of R245fa under different operating conditions within the ORC cycle.

R245fa's Behaviour in ORC Cycle:

R245fa possesses advantageous properties for ORC systems operating at low temperature: It is proficient in the low-temperature heat recovery spectrum, giving sufficient evaporation and condensation pressures for the energy transformation. The liquid is stable in the conventional ORC operating pressures and temperatures, hence providing good thermal stability and causing little decomposition during long operational periods.

Fluid Property Calculation for the Evaporator:

To represent the heat transfer inside the evaporator, the thermodynamic characteristics of R245fa are calculated at inlet and outlet of evaporator by simulation method. This enthalpy change between these two points is the heat gain by the fluid, which, in turn, is utilized for doing work in the expander through the cycle.

- Inlet State: The working fluid at the inlet is normally in a state of saturated or subcooled liquid.
- Outlet State: This fluid at outlet is most commonly a saturated vapour or a superheated vapour depending on heat source and pressure conditions.

It is possible to conduct the thermodynamic state calculations using CoolProp ensuring the perfect performance of the evaporator through accurate modeling just by entering the needed inputs.

In this low-temperature ORC system, R245fa was selected as the working fluid for its properties like low GWP, low boiling point, and thermal stability. Extensive and accurate modeling of R245fa thermodynamic properties can be done with CoolProp in MATLAB. These properties are essential in forecasting heat transfer and pressure drop throughout ORC cycle, specifically in the evaporator region. The ORC cycle model's capability to perform accurate property calculations allows it to introduce twisted tape inserts, which will consequently lead to performance analysis and optimization.

Table 1. System Parameters for ORC Setup

Parameter	Value
Working Fluid	R245fa
Evaporator Temperature	80 °C
Condenser Temperature	30 °C
Heat Source Temperature	120 °C
Working Fluid Mass Flow Rate	0.5 kg/s
Pump Efficiency	75%
Turbine Efficiency	80%
Tube Diameter	25 mm
Evaporator Length	5 m
Number of Tubes	10
Twist Ratio Range	2 to 10

The key parameters used in the simulation of the ORC system during this study are detailed in Table 1. These parameters include selection of R245fa as the working fluid, temperature of heat source as well as the temperatures at the evaporator and the condenser. Furthermore, table reflects mass flow rate of working fluid, efficiencies of both pump and turbine, and configuration of the evaporator including parameters such as tube diameter, length, and number. The twist ratio specifies the extent of twisted tape inserts that are applied in system for enhancing heat transfer process. These parameters define basic configuration of system that will subsequently be used for the analysis and improvement of the ORC cycle with the application of twisted tape inserts.

4.2. ORC Cycle Model (0D)

In this part of the paper, the 0D (zero-dimensional) ORC cycle model development with Simulink has been discussed. The model consists of four main components which include pump, evaporator, expander, and condenser. All of these elements contribute to the overall effectiveness of the system.

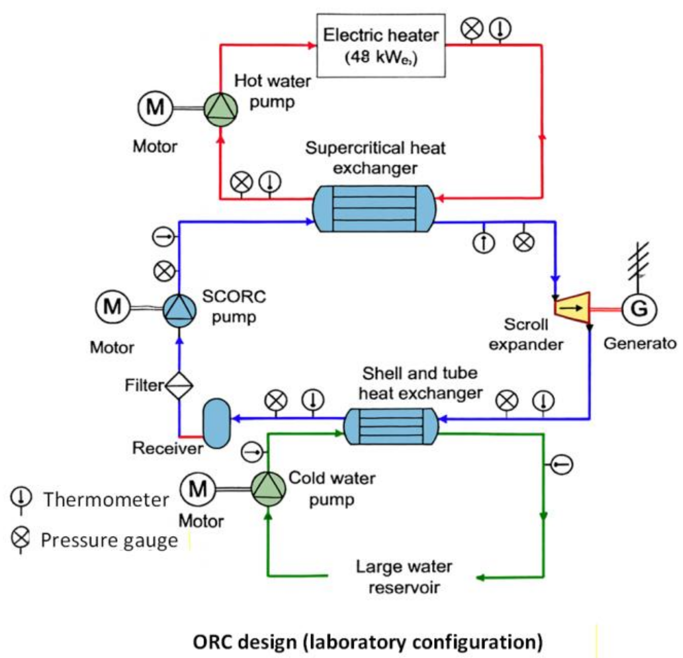


Figure 2. ORC Design (Laboratory Configuration)

Figure 2 illustrates the major parts of an ORC system: the scroll expander, which transforms heat energy into mechanical power, the supercritical heat exchanger, which transports heat from fluid to the ORC cycle, and the electric heater, which raises temperature of working fluid. The cold-water pump and SCORC pump together keep the fluid in motion through the system, whereas the shell-and-tube heat exchanger is responsible for heat exchange in cycle. Thermometers and pressure gauges are installed in the system to maintain optimal conditions throughout the trial and to record the performance.

4.2.1. Pump

The pump is responsible for raising the pressure of the working fluid (R245fa) from the condenser pressure to the evaporator pressure. The pump is modelled as an isentropic process (ideal) with an associated efficiency factor, which accounts for the real-world performance of the pump.

- **Input:** The pump receives working fluid at saturated liquid state from condenser at low pressure.
- **Output**: The pump raises pressure of fluid, which is then delivered to the evaporator.

The power consumed by the pump, W_p, is given by the following Eqn 2

$$W_p = \dot{m}\Delta h/\eta_p \tag{2}$$

Where, $\dot{m}$ is mass flow rate of a working fluid, Δh is change in enthalpy between the inlet and outlet of the pump, η_p is pump efficiency, which accounts for losses in the pump.

This power consumption is an important part of cycle, as it directly affects net power output of a system.

4.2.2. Evaporator

Heat Transfer: The heat transfer process is governed by temperature difference between hot side and cold side. The twisted tape inserts augment the turbulence of the flow, improving the heat transfer rate and causing an increase in the Nusselt number.

Pressure Drop: The twisted tapes also introduce a pressure drop due to increased friction and turbulence. The pressure drop is calculated by incorporating empirical correlations specific to twisted tape inserts, which relate the twist ratio, Reynolds number, and Prandtl number to heat transfer and pressure loss. This overall heat absorbed by the working fluid is given by the energy balance, which is given in Eqn 3

$$Q_{\text{in}} = \dot{m}(h_{\text{out}} - h_{\text{in}}) \tag{3}$$

Where, Q_{in} is the heat absorbed by working fluid, h_{out} and h_{in} are enthalpies at the outlet and inlet of evaporator, respectively.

4.2.3. Expander

The expander (typically a turbine) extracts work from the high-pressure vapor leaving the evaporator. The expansion process is assumed to be isentropic (ideal), with an efficiency factor η_t to account for real-world deviations from the ideal process.

- Input: The expander receives the high-pressure vapor from the evaporator.

- Output: The working fluid is expanded to a low-pressure state at condenser pressure.

The work produced by the expander, W_{er} is calculated as given in Eqn 4

$$W_e = \dot{m}(h_{\text{in}} - h_{\text{out},is})/\eta_t \quad (4)$$

Where: h_{in} is the enthalpy at the inlet of the expander, $h_{\text{out},\text{is}}$ is the isentropic enthalpy at the outlet of the expander, η_t is the expander efficiency, which accounts for the losses during the expansion process.

4.2.4. Condenser

In the condenser, the working fluid gives away its heat to the environment and transforms back into a liquid again. To determine the heat rejection the condenser model applies an energy balance, which guarantees that the amount of heat the fluid has released is same as heat absorbed in the evaporator.

- Input: The working fluid enters condenser as a saturated vapor.
- Output: It working fluid exits condenser as a saturated liquid at low pressure.

The heat rejected by the condenser, Q_{out}, is given in Eqn 5

$$Q_{\text{out}} = \dot{m}(h_{\text{in}} - h_{\text{out}}) \quad (5)$$

Where: h_{in} and h_{out} are the enthalpies at the inlet and outlet of the condenser, respectively.

The rejection of heat plays a very important role in evaluation of total performance of system since it has an impact on thermal and exergy efficiency of the cycle.

Output: Net Power, Thermal Efficiency, and Exergy Efficiency. Finally, overall net power output W_{net} of system is calculated as difference between power produced by expander and the power consumed by pump, which is given in Eqn 6

$$W_{\text{net}} = W_e - W_p \quad (6)$$

This value shows the net power performance produced by the ORC system.

The thermal efficiency η_{th} of the cycle is defined as ratio of net power output to total heat input, which is given in Eqn 7

$$\eta_{th} = \frac{W}{Q_{im}} \quad (7)$$

Exergy efficiency η_{ex} represents the portion of the input energy that is converted into useful work. It is given by Eqn 8

$$\eta_{ex} = \frac{W_{\text{net}}}{Q_{\text{in}} - Q_{\text{out}}} \quad (8)$$

The parameters generated through this process reveal the comprehensive functioning of the ORC system and also act as important indicators for evaluating how twisted tape inserts have influenced heat transfer and pressure drop characteristics in evaporator.

This performance simulation of the ORC system with different operating conditions relies on 0D ORC cycle model which consists of the pump, evaporator, expander and condenser in Simulink. The relations of twisted tape inserts, which are very important in improving the performance of ORC, are more accurately predicted by the evaporator model with correlations that assist in estimating the heat transfer and pressure drop. The model gives essential information about the low-temperature ORC system development by evaluating effects of twisted tape inserts on net power, thermal efficiency, and exergy efficiency.

The 0D ORC model was developed under steady-state conditions by neglecting external heat losses and minor pipeline pressure losses. Constant evaporator and condenser temperatures were maintained, while fixed isentropic efficiencies were considered for the pump and expander to ensure computational simplicity and thermodynamic consistency.

4.3. Evaporator Model (1D Control-Volume Approach)

The working fluid enters the system and is transformed into vapor in the evaporator, the main component of the ORC, through the heat source; thus, the evaporator is the most crucial part of the ORC. The 1D control-volume method is used in the modelling of the evaporator internal pressure drop and heat transfer. It is in this process that evaporator is divided into N control volumes (CVs), with each of the control volumes representing a small or small part of the evaporator tube. The flowing working fluid passes through the system, and the length of each control volume equals a small incremental segment of the evaporator, which, in turn, allows computing the properties of the fluid and energy very accurately.

Discretisation into Control Volumes (CVs)

Each of the N control volumes (CVs) that make up the evaporator represents a small part of the evaporator tube. The working fluid flowing through these CVs is considered one-dimensional since essential parameters such as temperature, pressure, and enthalpy vary along length of tube. The control volume method enables the carrying out of local calculations for energy balance, pressure drop, and heat transport in every segment.

Each control volume is characterized by: Inlet properties (temperature, pressure, enthalpy) at the start of the CV, Outlet properties (temperature, pressure, enthalpy) at the end of the CV, and the incremental length of the tube Δx.

Energy Balance for Local Enthalpy Changes

An energy balance is performed across each control volume to determine change in enthalpy of working fluid as it flows through evaporator. The change in enthalpy (Δh) is directly related to the heat absorbed from the heat source. For each control volume, the energy balance is written as given in Eqn 9:

$$\dot{Q} = m \cdot (h_{\text{out}} - h_{\text{in}}) \tag{9}$$

Where: $\dot{Q}$ is the rate of heat absorbed by fluid in each control volume, $\dot{m}$ is mass flow rate of the working fluid, h_{out} and h_{in} are enthalpies at outlet and inlet of control volume, respectively.

It local enthalpy changes are calculated from temperature and pressure values at inlet and outlet of each control volume. These values can be determined using CoolProp or other thermodynamic property tables, ensuring that the fluid properties are accurate for the given operating conditions.

Heat Transfer: Twisted Tape-Enhanced Correlations

The twisted tape inserts augment turbulence in the fluid flow, thereby enhancing HTC. The Nusselt number (Nu), which characterises rate of heat transfer in evaporator, is significantly increased by presence of the twisted tape inserts.

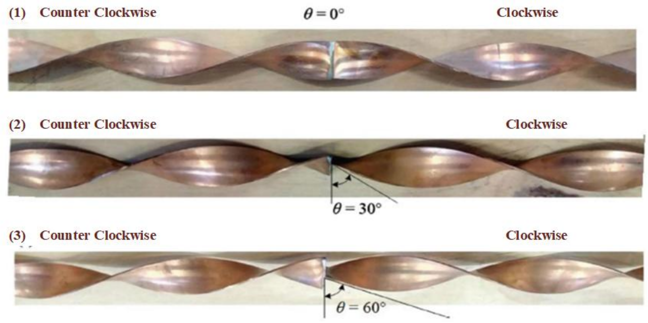


Figure 3. Sample Twisted Tape Insert Designs with Twist Angles

Figure 3 illustrates the different varieties of twisted tape inserts designed to improve heat transfer in ORC systems. This twist angle (θ) is the main factor that determines how much turbulence and mixing there will be in the heat exchanger, and that directly influences both heat transfer coefficient and pressure drop. The first design (1) with an angle of 0° gives the chance to compare the inserts with and without twist concerning heat transfer and fluid flows. With the increasing twist angle to 30° and 60° (designs 2 and 3), the inserts have an opposite effect due to the enlarged turbulence; they do increase heat transfer, but at a high price of pressure drop. Eventually, ORC system would require some adjustments to operate very efficiently under those conditions.

To model heat transfer enhancement due to twisted tape, we use empirical correlations that modify the Nusselt number for flow inside a tube with twisted tape inserts. These correlations are functions of (Re), the (Pr), and twist ratio of the inserts. The Nusselt number is used to calculate heat transfer coefficient is given in Eqn 10

$$\text{Nusselt number (Nu): } Nu = Nu_{\text{smooth}} \cdot E_{Nu}(\text{Re}, \text{Pr}, y) \tag{10}$$

Where: Nu_{smooth} is the Nusselt number for flow in a smooth tube (without inserts), $E_{Nu}(\text{Re}, \text{Pr}, y)$ is the enhancement factor due to the twisted tape, which is a function of: (Re): A dimensionless number that characterises the flow regime (laminar, transition, or turbulent), (Pr): A dimensionless number that relates the fluid's kinematic viscosity to its thermal diffusivity, Twist ratio (y): A ratio that characterises the geometry of the twisted tape, influencing flow dynamics and heat transfer. The thermal performance of the ORC evaporator is governed by the combined interaction between thermal conditions, flow behaviour, and twisted tape geometry. Variations in operating temperature directly influence fluid viscosity, thermal conductivity, and heat absorption characteristics, thereby affecting the Reynolds and Prandtl numbers within the evaporator. Simultaneously, the flow pattern changes from stable to highly turbulent conditions depending on the Reynolds number and twist ratio. Lower twist ratios generate stronger swirl intensity and secondary flow structures, which improve fluid mixing and thermal boundary-layer disruption, resulting in higher heat-transfer rates. However, excessive turbulence also increases frictional resistance and pressure losses. Therefore, the relationship among thermal conditions, flow patterns, and twist ratio is strongly interdependent, where modifications in one parameter significantly influence the overall thermal-hydraulic performance and energy efficiency of the ORC system.

This heat transfer rate for each control volume can then be calculated as given in Eqn 11

$$Q = h_{avg} \cdot A_{cv} \cdot \Delta T_{lm} \tag{11}$$

Where: h_{avg} is the average heat transfer coefficient for each control volume, calculated using the Nusselt number and fluid properties, A_{cv} is heat transfer surface area control volume, ΔT_{lm} is logarithmic mean temperature difference between the fluid and heat source over control volume. The twisted tape geometry significantly influences turbulence intensity, secondary flow generation, and fluid mixing behaviour within the evaporator tube. Lower twist ratios generate stronger swirl flow and greater turbulence intensity, which enhance disruption of the thermal boundary layer and improve convective heat transfer performance. At higher Reynolds number regimes, the intensified mixing between the core fluid and near-wall regions further increases the Nusselt number and overall heat-transfer coefficient. However, excessive turbulence also increases frictional resistance and pressure losses across the evaporator. Under laminar and transitional Reynolds number conditions, the twisted tape inserts promote earlier flow disturbance and improve thermal transport stability, while under turbulent regimes they strengthen vortex formation and heat-transfer augmentation throughout the ORC evaporator system.

Twisted tape inserts were selected because they provide passive heat-transfer enhancement without requiring external power input or complex mechanical modifications. The swirl flow generated by the inserts improves fluid mixing and thermal boundary-layer disruption, thereby increasing convective heat transfer effectiveness inside the evaporator. In addition, the thermophysical properties of the selected working fluid, including thermal conductivity, viscosity, and specific heat capacity, significantly influence the swirl-induced heat-transfer enhancement and thermal transport behaviour within the ORC system.

Pressure Drop: Twisted Tape-Enhanced Correlations

The introduction of twisted tape inserts also causes a pressure drop in the fluid due to increased friction and turbulence. The pressure drop can be calculated using empirical models that account for the additional resistance caused by the inserts.

The total pressure drop in each control volume is a combination of frictional losses and acceleration losses. The frictional pressure drop is modified by the twisted tape inserts, which increase the friction factor and thus the pressure drop. The total pressure drop for each control volume is given in Eqn 12

$$\Delta p = f \cdot \frac{L_{cm}}{D_h} \cdot \frac{\theta v^2}{2} \tag{12}$$

Where: f is friction factor that accounts for additional losses due to the twisted tape, L_{cv} is length of control volume, D_h is hydraulic diameter of tube, ρ is the density of fluid, v is velocity of the fluid in control volume, friction factor f is influenced by twisted tape geometry, the Reynolds number, and flow conditions in tube.

This 1D control-volume method serves as an effective tool to compute in-depth heat transfer and pressure loss in the low-temperature ORC evaporator that has twisted tape inserts. Through the division of the evaporator into several control volumes, it becomes possible to precisely represent the local enthalpy variations, local heat transfer being enhanced and local pressure drop for each portion. The empirical correlations for twisted tape inserts can be directly applied to the Nusselt number, heat transfer coefficient, and pressure drop for calculative purposesall these variables being the main ones for optimising the evaporator performance in the ORC system. It use of this model for evaluating impact of the twisted tape inserts and conducting optimisation studies will be conducive to the overall improvement of the ORC cycle performance. The 1D evaporator model further assumed one-dimensional fluid flow with uniform thermophysical properties inside each control volume. Radial heat conduction, fouling effects, and gravitational influences were neglected, while twisted tape behaviour was represented using empirical correlations to reduce computational complexity while maintaining prediction accuracy.

4.4. Deep Learning Model for Prediction

Here, discusses application of the CFD to ORC system modelling and its advantages in predicting and optimizing fluid flow, as well as heat transfer in the evaporator. The twisted tape inserts are also incorporated in CFD modelling since modelling is concerned with the key parameters. In this framework, CFD analysis was employed for performance prediction; instead, the thermodynamic simulation model was used to generate the dataset required for deep learning training and evaluation. The DNN utilised simulation-generated thermodynamic and flow parameters to predict ORC system behaviour, while the evaporator modelling approach captured the influence of twisted tape inserts on heat transfer and pressure characteristics. This distinction ensures consistency between the simulation-based modelling framework and the deep learning prediction process used for system evaluation.

4.4.1. Data Collection

The Deep Learning model's data was obtained from the ORC system simulation runs. Among the basic operating and design parameters that were varied were the evaporator temperature (80 °C), condenser temperature (30 °C), heat-source temperature (120 °C), working-fluid mass flow rate (0.5 kg/s), tube diameter (25 mm), evaporator length (5 m), and twist ratios between 2 and 10. Under each scenario, the model produced values for several parameters like Nusselt number, friction factor, thermal performance factor, pressure drop, net power, thermal efficiency, and exergy efficiency. This is an underlying data set made up of many pairs of input and output, which was employed to train the Deep Learning model, which could subsequently forecast ORC performance across a wide variety of situations.

4.4.2. Data Preprocessing

Data preparation essentially constitutes the basis upon which DNNs are built and hence the whole machine learning model would be learnt. In the present work, the simulated data obtained from the ORC cycle model simulation, which included effect of twisted tape inserts on heat transfer and pressure drop, were employed as the input for the DNN model. Normalisation and scaling of all input and output variables is what preprocessing does; therefore, it simplifies the model training and at the same time, it increases the accuracy of predictions.

Normalisation of Input and Output Variables

Before starting with the training of the DNN, it is important to normalize both the input and output variables to a common scale, usually between 0 and 1. This normalization guarantees that the learning process is not dominated by any single variable because of its higher value range. Additionally, it speeds up the convergence of neural network during training phase.

Normalisation is typically performed using the following standard formula for min-max normalisation, which is given in Eqn 13

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{13}$$

Where: x is the original value of the variable, x' is normalised value, $\min(x)$ and $\max(x)$ are the minimum and maximum values of variable x in dataset.

This formula transforms values into a range between 0 and 1, which is particularly useful for neural networks, as it reduces the chances of exploding or vanishing gradients, leading to more stable and faster training.

Normalisation of Input Variables

For the ORC system, the input variables include: Twist ratio (y): The ratio that defines the geometry of the twisted tape insert, Reynolds number (Re): A dimensionless number that characterizes flow regime, Prandtl number (Pr): Another dimensionless number related to the fluid's thermal and kinematic properties, Flow rate: this is a mass flow rate of the working fluid, typically denoted $\dot{m}$, Temperature: Inlet temperature of the working fluid.

These input variables have varying ranges of values. For instance, the twist ratio y typically ranges from 1 to 10, the Reynolds number Re is one of the parameters that can change very much due to the different flow situations (laminar, transition, or turbulent). To get these variables in the same range, the following steps are taken:

- First find the minimum and maximum values for each input variable in training dataset.
- Then use the min-max normalization formula to bring every variable to a range of [0,1].

This process will prevent the neural network from favoring one variable over others and will thus enable it to learn the pattern between all variables in the same way.

Normalisation of Output Variables

The output variables, which are the key performance indicators of the ORC system, include:

- Heat transfer coefficient (HTC): This represents rate at which heat is transferred between working fluid and heat source.
- Pressure drops (Δp): The pressure difference across the evaporator is due to frictional losses and turbulence caused by the twisted tape inserts.
- Thermal performance factor (TPF): A performance metric that compares the enhancement in heat transfer to increase in pressure drop due to twisted tape inserts.
- Net power output: It amount of useful mechanical power produced by ORC system.
- Exergy efficiency: The efficiency of the cycle, accounting for both energy and irreversibility.

These output variables may have different ranges and units, so normalisation is equally important for them. The same min-max normalisation formula is applied to the output variables, which is given in Eqn 14

$$y' = \frac{y - \min(y)}{\max(y) - \min(y)} \tag{14}$$

Where: y is original value a output variable, y' is the normalised output, $\min(y)$ and $\max(y)$ are the minimum and maximum values output variable dataset.

By normalising the outputs, we ensure that the DNN can process them more effectively and improve the accuracy of predictions.

Handling Categorical or Missing Data

In some cases, the dataset may include categorical variables or missing values. Although this research primarily focuses on numerical variables, if categorical data (e.g., fluid types) were present, they would be encoded using techniques such as one-hot encoding. Missing values are typically handled by imputation (replacing with mean, median, or using a model-based approach), or rows with missing data can be discarded, depending on the importance of the missing data.

Splitting Data into Training, Validation, and Test Sets

Once the information is normalised, it is essential to divide it into training, validation, and test sets. This training set is used to train model, validation set is used to tune model hyperparameters, and test set is used to evaluate model's performance on unseen data.

A common split ratio is: Training set: 70-80% of data, Validation set: 10-15% of data, Test set: 10-15% of data.

The model's capability of not just memorizing the training data but also of being able to infer correctly from new unknown data is thus assured.

One of the key techniques in data preprocessing is normalisation, which has a vital impact on the training process of the DNN. When we apply normalisation to both the input and output variables, we make the DNN learning process faster and more stable as well as making sure that the training is efficient. The systematic approach to dividing the data and treating the missing values guarantees that model is trained on the best quality data which in turn results in more accurate and dependable forecasts of the heat transfer, pressure drop, and overall performance ORC system with twisted tape inserts.

4.4.3. Model Architecture: Training a Deep Neural Network (DNN) in MATLAB

Figure 4 shows the DNN that is applied to the forecasting and optimization of the ORC system. The operational parameters which include temperature, flow rate, and twist ratio are each represented by the six neurons (X1-X6) in the input layer. The three hidden layers with 100, 500, and 200 neurons process the inputs. The output layer is made of two neurons (Y1 and Y2) and it reveals the predicted values of heat transfer coefficient and pressures drop, which are key performance metrics. The proposed DNN architecture proves to be highly effective for predicting and optimising ORC system performance under different operating conditions.

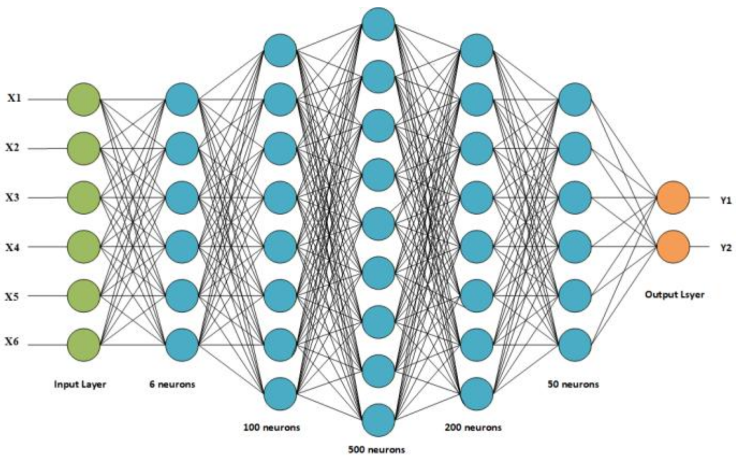


Figure 4. Deep Neural Network (DNN) Architecture

In this research work, a main aim of employing a DNN is to forecast efficiency of a low-temperature ORC system associated with twisted tape inserts. The model will grasp the intricate interconnections between different input factors (like twist ratio, Reynolds number, and flow rate) and output factors (like heat transfer coefficient, pressure drop, and net power). The DNN is structured to cope with these nonlinear relations and produce reliable predictions regarding the performance of the system. The DNN architecture with multiple hidden layers and varying neuron counts was designed to capture the highly nonlinear thermodynamic and flow interactions present in the ORC system. The larger hidden layers improve the model's capability to learn complex relationships among operating parameters such as twist ratio, Reynolds number, temperature, and pressure drop, while the deeper network structure enhances prediction accuracy for heat-transfer and efficiency characteristics under varying operating conditions.

Inputs and Outputs of the Model

The DNN's input variables are the backbone of the ORC system's operational conditions. Among these inputs, the twist ratio, Reynolds number, Prandtl number, flow rate, and temperature at the evaporator inlet are included. These variables are of utmost significance as they determine flow and heat transfer behaviour of working fluid system. The twist ratio, in particular, has a direct effect on heat transfer characteristics, while Reynolds and Prandtl numbers, in turn, identify the flow regime and the heat transfer capacity.

The output variables are the performance metrics that mirror in a very direct manner efficiency and effectiveness of ORC system. Among these are following:

- Nusselt number (Nu), which indicates the amount of heat transfer in the evaporator.
- Heat transfer coefficient (HTC), which gives rate of heat transfer between fluid and the heat source.
- Pressure drop (Δp), representing the resistance to flow due to friction and turbulence in the system.
- TPF, which compares heat transfer enhancement to the increased pressure drop.
- Net power produced by the system, calculated as difference between the power extracted from expander and the power consumed by a pump.
- Exergy refers to the efficiency with which a system translates its thermal energy into useful work.

DNN Architecture

This architecture is composed of three primary components: input layer, numerous hidden layers and output layer. Each layer is important in its own way for converting the input data into useful predictions that will be the performance metrics of the system.

Input Layer: Operating parameters such as twist ratio, Reynolds number, Prandtl number, flow rate, and temperature are given to the input layer. A different input node is allotted to every variable. The DNN will comprehend the impact of each input on the behavior of the system, which will enable it to model the complex interplay among them.

Hidden Layers: The DNN is composed of several hidden layers in which neurons (nodes) carry out the processing of the input data through applying weights, summation and then the use of a nonlinear activation function. A hidden layer adds a level of abstraction to the model and thus helps it discover complex data patterns and relationships.

The ReLU is used as activation function in the hidden layers, defined as given in Eqn 15

$$\mathrm{ReLU}(y) = \max(0, y) \quad (15)$$

The ReLU function ensures that the network can learn nonlinear relationships and provides better convergence properties by avoiding the vanishing gradient problem, which is common with other activation functions.

Output Layer: The layer responsible for the output comprises of neurons that reflect the estimated performance indicators of the ORC system, including Heat transfer coefficient, pressure drop, and Nusselt number. The output layer applies a linear activation function, which is precisely described in Eqn 16.

$$\text{Linear}\ (x) = x \tag{16}$$

This capability permits the generation of values that are just as good as continuous ones, thus, they are ideal for the prediction of metrics, for instance, net power and exergy efficiency which require a diversity of real values as output.

Training the DNN: The training procedure uses backpropagation along with gradient descent to optimise the weights of the neurons in the hidden layers as the optimisation algorithm. The loss function quantifies the deviation of predicted values from actual target values, and model modifies weights in a way such that the deviation is minimized. For regression tasks, such as this one, the MSE is the most popular loss function and it has a mathematical definition that can be found in Eqn 17.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(y_{\text{true}}^{(i)} - y_{\text{pred}}^{(i)}\right)^2 \tag{17}$$

Where: $y_{\text{true}}^{(i)}$ is the true value for the i-th data point, $y_{\text{pred}}^{(i)}$ of predicted value for the i-th data point, n a total number of data points in the training set.

The model employs either gradient descent or Adam optimizer to alter network’s weights in order to reduce MSE. Adam, one of the well-known optimization algorithms, not only varies the learning rate dynamically but also utilizes the benefits of both Adagrad and RMSprop, thus resulting in quicker convergence.

Loss Function and Optimisation

The DNN during its training process makes changes to the weights, first by estimating gradient of a loss function in relation to each weight, and then it updates weights with help of the optimisation algorithm. The purpose of this whole process is to reduce the loss function step by step, and meanwhile the model gets trained to predict the performance metrics very accurately.

After the model has been trained, the DNN is tested on validation set to adjust hyperparameters of the model. Following the training and validation stages, test set is used to assess final model which offers an objective measure of its ability to perform on new, unseen data.

Evaluation and Validation

The last step in the model's performance assessment is to match its predictions to the actual values in test set. The MAE, which indicates mean absolute deviation between predicted and actual values, and R-squared (R^2) value, which shows how well model accounts for variance data, are among the most widely used evaluation metrics.

The DNN structure utilized for the ORC system which includes twisted tape inserts comprises several hidden layers employing ReLU activation to uncover intricate, non-linear interactions among the input variables (like twist ratio and Reynolds number) and the output variables. Not only does training the DNN with backpropagation and gradient descent make a model capable of predicting key performance metrics ORC system, but also architecture, loss function, and training process grant the model good generalization to the unseen data, thus empowering it to optimize and predict the ORC system performance under different operational conditions.

Model Training

The DNN's training is based on the simulated data output from the ORC cycle model to allow the network to grasp the connection between input parameters (for instance, aspect ratio, Reynolds number, flow rate, and others) and output parameters (like heat transfer coefficient, pressure drop, and net power). The ultimate purpose of the training procedure is to reduce the prediction errors and to refine the DNN's capability to provide accurate forecasts of the system's performance.

Data Split

Prior to the training process of DNN, the simulated data is divided into three sets which are named as training, validation, and test sets.

⇒ 1.Training Set: DNN weights are only adjusted with this part of the data during the whole training process. Its portion is usually the largest which accounts for around 70-80% of data.

⇒ 2.Validation Set: Hyperparameters of model are adjusted and overfitting is prevented with this subset. The optimal configuration is identified through the model's performance on this set.

⇒ 3.Test Set: The last subset is utilized to assess a model's capacity to generalise on new data that has not been seen before. It indicates the extent to which the trained model can forecast real-world scenarios.

The splitting of the data often follows a ratio of 70% to training, 15% to validation, and 15% to testing, but this can be modified according to the size of available data.

Training the Model

First, data is divided into two parts first part is used for DNN training that is done through the backpropagation and gradient descent methods that help to change the network's weights to the best possible ones. Backpropagation is the main approach used to find out gradients a loss function concerning model's parameters (weights), and gradient descent is applied to adjust the weights against the gradients, thus reducing the loss.

The loss function commonly used for regression tasks is the MSE, given in Eqn 18

$$\mathrm{MSE}=\frac{1}{n}\sum_{i=1}^{n}\left(y_{\mathrm{true}}^{(i)}-y_{\mathrm{pred}}^{(i)}\right)^{2} \tag{18}$$

Where $y_{\mathrm{true}}^{(i)}$ represents the true value, $y_{\mathrm{pred}}^{(i)}$ is predicted value, and n is number of samples. The MSE minimisation is purpose that weight update via an optimisation algorithm brings about as a result of the MSE which is ascribed to the loss function. The methods for loss function minimisation include gradient descent and advanced algorithms like Adam. These approaches make small adjustments to the weights at each step by obtaining the gradients and shifting the weights downwards in the steepest direction.

4.4.4. Hyperparameter Tuning

In order to optimise the performance of the DNN, it is important to tune various hyperparameters including the learning rate, number of epochs, batcsize, and the number of hidden layers.

- Learning rate (η): This parameter influences how much the weights are updated relative to the gradient. A learning rate that is too big, for example, may cause model to simply converge too quickly to some sub-optimal solution, whereas a learning rate that is too small can slow down training significantly.
- Number of epochs: This hyperparameter informs the number of times that the entire dataset is passed through the network. Training with too few epochs results in underfitting while training with too many epochs will lead to overfitting.
- Batch size: This hyperparameter refers to number of training examples to use to calculate gradients on each update. During stochastic gradient descent training of deep learning models smaller batch sizes provide a more informative estimate of the gradients, while larger batch sizes can speed up training process but typically provide less informative gradients.

Hyperparameter tuning is typically done by evaluating model performance on validation set for a variation of combinations of hyperparameter settings. Search methods such as random search or grid search are typically used to find the best values for the hyperparameters.

During training, DNN is trained via splitting data into training, validation, and test sets and applying backpropagation and gradient descent to change the weights within the network. The model is trained to minimise the (MSE) and adjusted with hyperparameter optimisation to explore better performance. The learning process occurs through multiple iterations of the training, validating, and testing processes, where the model learns to predict performance from the ORC system with twisted tape inserts correctly. The output of these predictions provides directional support for optimisation and the redesign of the ORC systems.

4.5. ORC Cycle Integration with Deep Learning

The trained DNN was integrated with the Simulink-based ORC model through a continuous data exchange framework, where simulation outputs generated from the thermodynamic model were supplied as inputs to the neural network for real-time prediction. The DNN processed operating parameters such as flow rate, temperature, and twist ratio to rapidly estimate system performance indicators, thereby improving simulation efficiency and supporting dynamic ORC system evaluation within the MATLAB-Simulink environment. The trained DNN model takes the inputs and predicts important outputs such as heat transfer coefficient (HTC), pressure drop (Δp), and Nusselt number (Nu).

Predicted values is used to find the exergy efficiency and net power as mentioned in detail. Net Power is computed by taking difference between Expander work W_e and the pump works W_p, which is given in Eqn 19

$$W_{\text{net}} = W_e - W_p \tag{19}$$

Where does the expander work W_e is calculated using a enthalpy difference between inlet and outlet expander, and pump work W_p is determined using the enthalpy difference across the pump. The exergy efficiency η_{ex} is then calculated as given in Eqn 20

$$\eta_{\text{ex}} = \frac{W_{\text{net}}}{Q_{\text{in}} - Q_{\text{out}}} \tag{20}$$

Where Q_{in} and Q_{out} are the heat input and heat rejection in the cycle, respectively. The DNN together with the Simulink model provides an accurate real-time evaluation and optimization of the performance of the system providing effective design choices and enhanced efficiencies for the ORC system with twisted tape inserts. The integration of the trained DNN with the Simulink-based ORC model significantly reduces computational time compared with repeated thermodynamic simulations and CFD-based analyses. Once trained, the DNN rapidly predicts key performance indicators, including heat transfer coefficient, pressure drop, and net power output, from operating parameters such as twist ratio, temperature, and flow rate. This capability enables efficient real-time performance evaluation and optimisation of the ORC system while maintaining high prediction accuracy.

4.6. Optimisation using Deep Learning

Using MATLAB's optimization toolbox, the ORC system with twisted tape inserts is optimized. A parametric sweep is used over the design variables that drive optimization, including twist ratio, mass flow rate, and varying scenarios (temperature and pressure scenarios, for example) to maximise net power output and thermal performance factor (TPF), while minimizing pressure drop across the evaporator.

An objective formulation that we would like to maximize as given in Eqn 21

$$\text{Objective } - \max(W_{\text{net}}, \text{TPF}) \text{ and } \min(\Delta p) \tag{21}$$

Where: W_{net} represents the net power output, TPF is the thermal performance factor that compensates for the increased pressure drop with heat transfer enhancement. Δp is the pressure drop.

To guarantee implementation in reality, there is limited allowed pressure drop and operating temperatures. The limited pressure drop is set not to go beyond a certain level while the temperatures are kept in the range that is both safe and effective for the ORC operation system, which is given in Eqn 22

$$\begin{gathered} \Delta p_{\max} \leq \Delta p \leq \Delta p_{\max,\text{ allowable}} \\ T_{\max} \leq T \leq T_{\min} \end{gathered} \tag{22}$$

The efficient and high-performance ORC system is achieved by determining the optimal values of the twist ratio, mass flow rate, and other operating conditions through solving this optimization problem.

5. Result and discussion

The results section presents an extensive evaluation of the ORC system based on simulation evaluation, deep learning-based prediction, and optimization. Results demonstrate the influence of twist ratios of the system performance and the optimization framework is proven to be effective in improving heat transfer, power output, and overall system efficiency. The outcomes also demonstrate the accuracy of the proposed DNN model under significant thermodynamic parameter conditions. The key findings indicate that lower twist ratios significantly improve heat transfer enhancement and net power generation, while higher twist ratios reduce pressure drop but slightly decrease thermal and exergy efficiencies. In addition, the proposed DNN-based optimisation framework achieved highly accurate prediction performance with R^2 values above 0.98 for most output parameters. The optimisation process further improved the ORC system performance by increasing the net power output to 4.672 kW and achieving a thermal performance factor of 1.6452 under optimal operating conditions.

Table 2. System Specifications for Model Development and Simulation

Component	Details
Storage	466 GB
Graphics Card	Intel(R) UHD Graphics 730 (128 MB)

Installed RAM	8.00 GB (Speed: 3200 MT/s)
Processor	12th Gen Intel(R) Core(TM) i5-12400 (2.50 GHz)
Device name	DESKTOP-6JDP8JE
Processor (Detailed)	12th Gen Intel(R) Core(TM) i5-12400 (2.50 GHz)
Installed RAM (Detailed)	8.00 GB (7.75 GB usable)
Device ID	0D4988B9-B481-42D4-B4AD-C051F531425A
Product ID	00331-10000-00001-AA589
System type	64-bit operating system, x64-based processor
Pen and touch	No pen or touch input is available for this display
software	MATLAB R2024b

Table 2 describes the hardware and software setup for the simulating, model training and model optimization tasks completed in this research project. A experiments were conducted on a full-system that included a 12th Gen Intel Core i5-12400 CPU, 8 GB of RAM, Intel UHD Graphics 730, and 466 GB of storage, on a 64-bit Operating System. MATLAB R2024b was used as the primary software environment for ORC simulation, data processing, and implementation of the deep learning models.

5.1. Simulated ORC Outputs: Heat Transfer and Efficiency Metrics

This subsection shows simulation of a performance of the ORC system at varying twist ratio conditions. The main heat exchange and efficiency parameters are examined to learn the influence of geometric changes on the power production, thermal properties, and the flow regimes within the evaporator space.

Table 3. Single Cycle Results for ORC System

Parameter	**Value**
Twist Ratio (y)	5
Net Power Output	2.68 kW
Pump Work	0.30 kW
Turbine Work	2.98 kW
Heat Input (Evaporator)	41.38 kW
Heat Rejected (Condenser)	38.70 kW
Thermal Efficiency	6.48%
Exergy Efficiency	26.81%
Evaporator Pressure Drop	2.06 kPa
Thermal Performance Factor	1.631
Average Reynolds Number	68049
Average Prandtl Number	5.4

Table 3 presents the simulated output results for one cycle of the ORC system with a twist ratio (y) of 5. The system net power is 2.68 kW with 0.30 kW of pump power consumption and 2.98 kW of turbine power consumption. The thermal efficiency and energy efficiency are 6.48% and 26.81% respectively. Of the total heat input of 41.38 kW to the evaporator, the condenser has rejected only 38.70 kW. The thermal performance factor (TPF) of 1.631 and a condenser pressure drop of 2.06 kPa demonstrate that the heat transfer has been significantly improved. The average Reynolds number, is 68049 and the Prandtl number is 5.4, these are good indicators of the fluid dynamics of the system at these operating conditions.

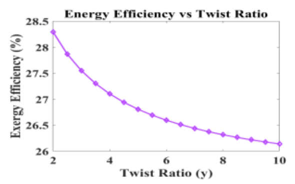
Table 4. Twisted Tape Variations

y	**W_net (kW)**	**η_th (%)**	**η_ex (%)**	**ΔP (kPa)**	**TPF**
2.0	3.07	6.84	28.29	3.25	1.680
2.5	2.95	6.73	27.87	2.82	1.664

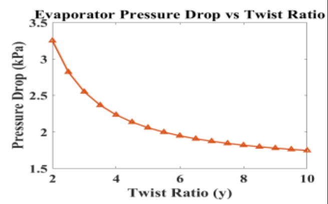
3.0	2.87	6.66	27.55	2.55	1.653
3.5	2.80	6.60	27.30	2.37	1.646
4.0	2.75	6.55	27.10	2.23	1.640
4.5	2.71	6.51	26.94	2.14	1.635
5.0	2.68	6.48	26.81	2.06	1.631
5.5	2.65	6.45	26.69	2.00	1.627
6.0	2.63	6.43	26.60	1.95	1.624
6.5	2.61	6.41	26.51	1.91	1.621
7.0	2.59	6.39	26.44	1.87	1.619
7.5	2.58	6.37	26.38	1.84	1.617
8.0	2.56	6.36	26.32	1.82	1.615
8.5	2.55	6.35	26.27	1.80	1.613
9.0	2.54	6.34	26.22	1.78	1.611
9.5	2.53	6.33	26.18	1.76	1.609
10.0	2.52	6.32	26.14	1.75	1.608

The performance of the ORC system at different twist ratios (y) is summarised in Table 4, which also indicates the primary performance metrics such as: net power output, which was measured based on the following: thermodynamic efficiency (ηth), exergetic efficiency (ηex), pressure drop at the evaporator (ΔP), and the thermal performance factor - TPF. The net power output dropped only slightly between a twist ratio of 2.0 to 10.0, equating to a decrease from 3.07 kW to 2.52 kW of net power output. Comparable to this range, thermal efficiency developers has similar output results with thermal efficiency decreasing from 6.84% to 6.32%, while energy efficiency drifted downward amounting from a reduction range of 28.29% to 26.14%. The opposite trend existed with pressure drop as compared to the twist ratio oppositely; thus, the minimum pressure drop recorded at a twist ratio of 10.0 was 1.75kPa. The thermal performance factor showed a decrement of 0.072 on average, while the overall loads fell below the derived estimates from the previous ratio ranges, from 1.680 to 1.608. Thus, illustrating that return rates decreased. The thermal performance factor (TPF) serves as an important trade-off indicator between heat-transfer enhancement and pressure-drop penalties within the ORC evaporator system. Higher TPF values indicate improved thermal enhancement with comparatively lower hydraulic losses, thereby assisting in identifying optimal twisted tape geometries for efficient and balanced system design.

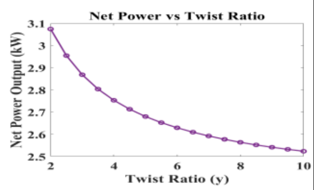
The results demonstrate the influence of twisted tape geometry on the thermal-hydraulic performance of the ORC evaporator. Lower twist ratios generate stronger swirl flow and turbulence, leading to higher heat transfer coefficients and improved net power output. However, these enhancements are accompanied by increased pressure drop due to greater frictional resistance. As the twist ratio increases, the pressure drop decreases, although a slight reduction in heat transfer enhancement and power generation is observed. Therefore, an appropriate balance between heat transfer coefficient improvement, pressure drop limitation, and net power maximisation is necessary to achieve optimal ORC system performance.



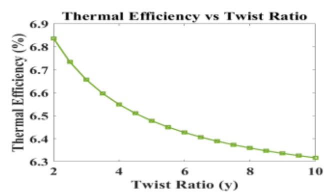
Energy Efficiency vs Twist Ratio



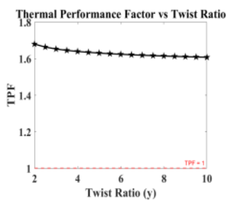
Evaporator Pressure Drop vs Twist Ratio



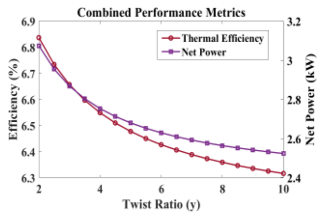
Net Power vs Twist Ratio



Thermal Efficiency vs Twist Ratio



Thermal Performance Factor vs Twist Ratio



Thermal Efficiency and Net Power vs Twist Ratio

Figure 5. ORC Simulated Outputs: Performance Metrics vs Twist Ratio

The six graphs and table demonstrate how the ORC system performs under different twist ratios (y). Figure 5 summarises the influence of twist ratio on ORC system performance. Increasing the twist ratio reduced the evaporator pressure drop while slightly decreasing the net power output, thermal efficiency, and exergy efficiency. The thermal performance factor remained relatively stable, indicating a balanced trade-off between heat-transfer enhancement and hydraulic losses across different operating conditions.

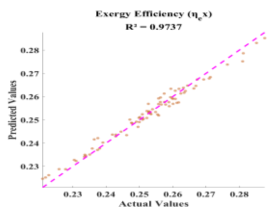
5.2. Model Output and Performance Results

Here, the Deep Learning model's capability to generate predictive accuracy is established by comparing true and estimated values of key ORCs. The results demonstrate that the model is capable of capturing nonlinear thermodynamic behaviour as embodied in power, efficiency and heat transfer parameters.

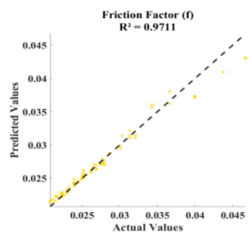
Table 5. Model Performance Metrics for Key ORC System Outputs

Parameter	MAE	RMSE	R²	MAPE
Nusselt Number (Nu)	12.633862	16.039846	0.989998	2.3143%
Friction Factor (f)	0.000644	0.001063	0.963431	2.0852%
Thermal Performance Factor (TPF)	0.002717	0.003589	0.985544	0.1673%
Net Power Output (W)	72.869179	90.775795	0.992463	2.9583%
Thermal Efficiency (η_th)	0.000526	0.000647	0.990109	0.8617%
Exergy Efficiency (η_ex)	0.001495	0.001845	0.981944	0.5923%

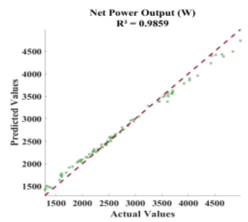
The performance metrics of the model outputs for the ORC system are reported in Table 5. The table presents MAE, RMSE, R^2, and MAPE results for e Nusselt number, friction factor, thermal performance factor, net power output, thermal efficiency, and exergy efficiency.



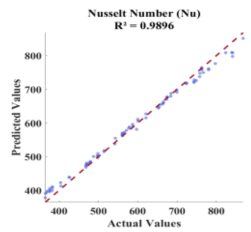
Exergy Efficiency vs Actual Values



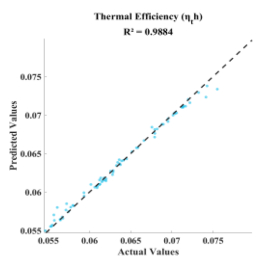
Friction Factor vs Actual Values



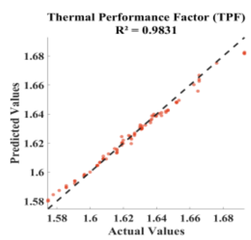
Net Power Output vs Actual Values



Nusselt Number (Nu) vs Actual Values



Thermal Efficiency (n_t) vs Actual Values



Thermal Performance Factor (TPF) vs Actual Values

Figure 6. Model Output Comparisons for ORC System Performance

Figure 6 demonstrates the strong agreement between the predicted and actual values for all key ORC performance parameters. The high R^2 values confirm that the proposed DNN model accurately captures the nonlinear thermodynamic behaviour of the ORC system and provides reliable prediction capability across varying operating conditions.

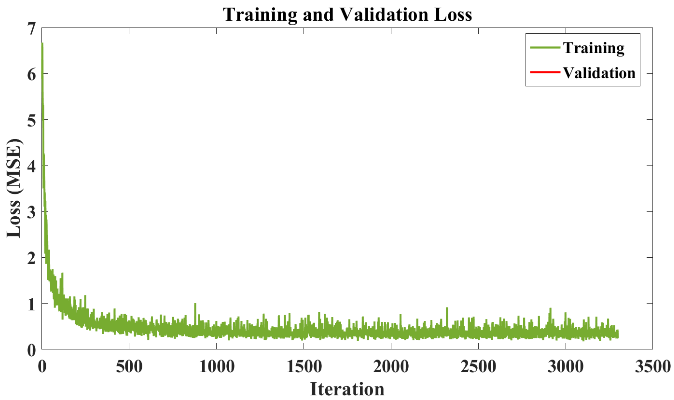


Figure 7. Training and Validation Loss (MSE) Curve

Figure 7 demonstrates history of training and validation loss of DNN as the process is optimised. The early iterations of the model have a steep drop in MSE, which shows rapid convergence as the model starts to grasp the underlying relationships. The loss usually stabilises and oscillates within a slim range after approximately 800-1000 iterations, indicating that the learning process is constant without divergence. This is because the training and validation curves are close, implying that there are minimal instances of overfitting and the model can generalise effectively.

Figure 8. Training Loss Progress

Figure 8 shows the trend in optimisation more intuitively in the case of smaller magnitudes of errors since the training loss is shown in a logarithmic form. The loss reduces gradually with the training duration in the log-scale representation, with minor increases that are difficult to observe in the linear-scale plot. The overall downward trend indicates constant optimisation despite the fact that stochastic gradient updates cause only small oscillations. This suggests that with further training, the DNN gradually improves its predictions and the resultant final model becomes more reliable.

5.3. Optimization Results: Performance Enhancement and System Optimization

The subsection presents the optimised performance metrics of ORC that is produced by the DNN-based optimisation framework. The outcomes demonstrate the positive impact of optimum operating conditions and design parameters on overall performance an ORC system through improvement of heat transfer, power output and efficiency.

Table 6. Optimised ORC Performance Metrics

Parameter	Value
Nusselt Number	769.108
Friction Factor	0.023497
TPF (Thermal Performance Factor)	1.6452
Net Power (kW)	4.672
Thermal Efficiency (%)	6.961
Exergy Efficiency (%)	25.160

Table 6 shows the optimal performance values obtained from the DNN-based optimisation. The system achieves a high Nusselt number with a low friction factor, indicating effective heat transfer with controlled pressure losses. The TPF of 1.6452 confirms a good trade-off between enhancement and flow resistance. Under these optimised conditions, the ORC delivers 4.672 kW net power with improved thermal and exergy efficiencies.

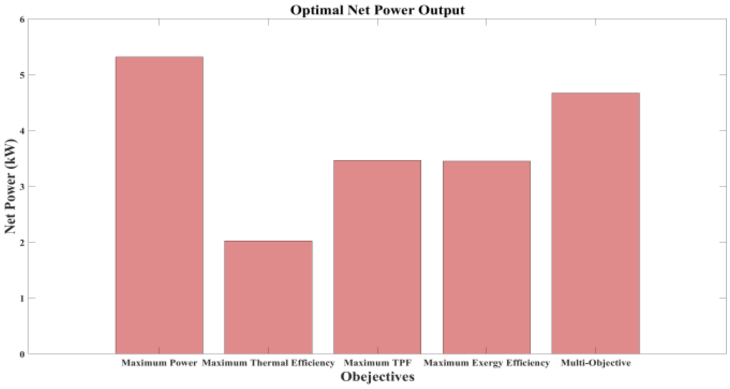


Figure 9. Optimal Net Power Output

Figure 9 shows optimism of net power production of optimisation process through DNN assistance. The operating parameters of the model are the ones that optimise the production of power by achieving a balance between increased heat transfer and the decreased pressure losses. This is following net power increment proves that the optimisation framework is working as it aims at enhancing the overall performance of the ORC system.

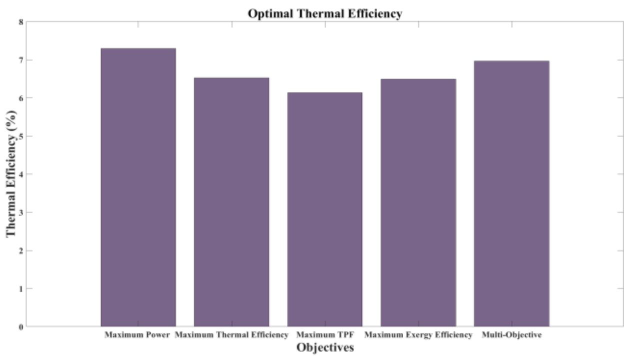


Figure 10. Optimal Thermal Efficiency

Figure 10 presents the optimised thermal efficiency achieved under the identified optimal operating conditions. The improvement in thermal efficiency demonstrates that the proposed optimisation policy effectively enhances the energy conversion capacity of the ORC system through improved heat utilisation and reduced thermodynamic losses. The optimised twist ratio and operating parameters improve turbulence intensity inside the evaporator, which increases the heat transfer rate while maintaining acceptable pressure losses. This enhancement enables more efficient thermal energy absorption by the working fluid and contributes to higher net power generation. Furthermore, the optimisation framework improves overall system stability and operational effectiveness by balancing heat transfer enhancement with flow resistance. These results confirm that the proposed DNN-assisted optimisation strategy can significantly improve energy utilisation efficiency and provide practical benefits for low-temperature waste heat recovery and industrial energy management applications.

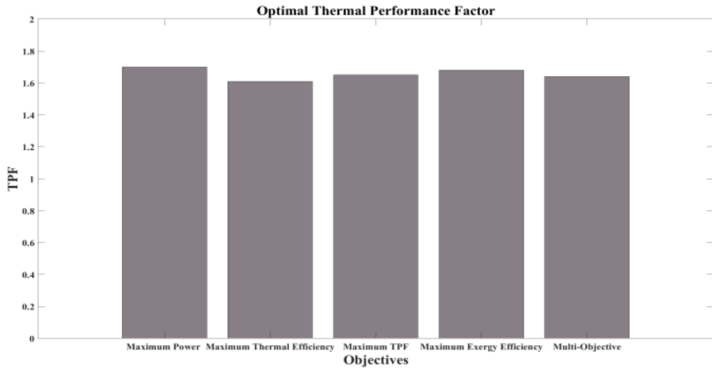


Figure 11. Optimal Thermal Performance Factor

Figure 11 shows the optimum thermal performance factor, which points to the trade-off between increased heat transfer and frictional penalties. The higher TPF value would ensure realistic and efficient ORC operation by making sure that the chosen operating settings maximise the heat transfer efficiency without generating an unreasonably high pressure drop.

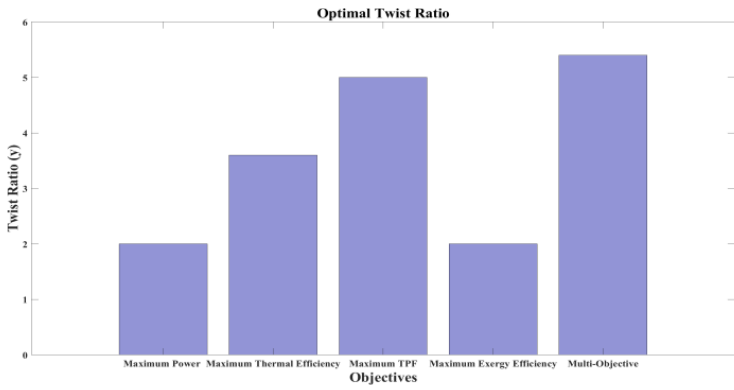


Figure 12. Optimal Twist Ratio

Figure 12 shows a best twist ratio that was obtained in process of optimisation. This twist ratio is the ideal ratio between turbulence-induced increase in heat transfer and the losses associated with friction. The results clearly demonstrate the significance of geometric optimization for system efficiency and evaporator performance.

5.4. Performance Comparison

As shown in Table 7, the performance comparison shows that the proposed DNN–ORC hybrid model performs better than all the other methods, while yielding the most accurate predictions. It is very stable with very low error, as it has the highest R2 and lowest MAE, and RMSE.

Table 7. Comparison of performance of proposed model with the existing ORC prediction methods

Method	MAE	RMSE	R²	MAPE
Proposed (DNN + ORC Hybrid Model)	**0.0027**	**0.0036**	**0.990**	**0.16%**
Data-Mining ORC Efficiency Model [24]	0.028	0.036	0.850	2.45%
ML-Based Vehicle ORC Optimisation [25]	0.015	0.021	0.920	1.10%

The MAPE value also supports its superior precision over the existing data-mining and ML-based ORC models. The results confirm that the framework proposed to predict ORC performance indicators will outdo traditional methods.

Table 8. Comparative Performance Evaluation of the Proposed DNN-ORC Framework and Baseline Models

Method	MAE	RMSE	R²	Training Time (min)	Scalability
Linear Regression	0.0241	0.0315	0.912	0.3	High
Random Forest	0.0114	0.0157	0.961	3.2	Medium
ANN	0.0068	0.0089	0.978	8.4	Medium
CFD-Based Model	0.0054	0.0072	0.982	480	Low
Proposed DNN-ORC	0.0027	0.0036	0.99	12.5	High

Table 8 presents a comparative evaluation of the proposed DNN-ORC framework against several baseline modelling approaches, including Linear Regression, Random Forest, Artificial Neural Network (ANN), and CFD-based modelling. The comparison considers predictive accuracy through MAE, RMSE, and R² metrics, together with computational efficiency measured by training time and scalability characteristics. The results demonstrate that the proposed DNN-ORC framework achieves the highest predictive accuracy while maintaining high scalability and substantially lower computational requirements than CFD-based approaches. These findings confirm the effectiveness of integrating deep learning with ORC system modelling for accurate and computationally efficient performance prediction and optimisation.

The comparison reveals clear differences among the evaluated approaches. Linear Regression achieved the shortest training time but exhibited the lowest predictive accuracy due to its inability to capture complex nonlinear relationships within the ORC system. Random Forest and ANN improved prediction accuracy by modelling nonlinear interactions, although their performance remained lower than that of the proposed DNN-ORC framework. The CFD-based model produced relatively high prediction accuracy; however, its computational cost was substantially higher, requiring significantly longer execution time and limiting its scalability for optimisation studies. In contrast, the proposed DNN-ORC framework achieved the highest predictive performance, with the lowest MAE and RMSE values and the highest R² value. Furthermore, its high scalability and moderate computational requirements make it suitable for large-scale optimisation and real-time performance evaluation of low-temperature ORC systems.

Table 9. Runtime Comparison of Different ORC Performance Evaluation Approaches

Method	Simulation Time per Case	Computational Requirement
Experimental Testing	2–4 h	Physical test setup
CFD Simulation	25 min	High
Thermodynamic ORC Model	18 s	Moderate
Proposed DNN Prediction	0.08 s	Low

Table 9 compares the computational runtime of different ORC performance evaluation approaches. Experimental investigations require several hours to complete, while CFD simulations significantly reduce testing time but still involve substantial computational effort. The thermodynamic model provides faster evaluation; however, the proposed DNN-ORC framework achieves the shortest execution time of only 0.08 s. This substantial reduction in runtime demonstrates the practical advantage of the proposed method for rapid performance prediction, optimisation, and real-time implementation.

5.5. Discussion

As indicated by the results, it was observed that ORC operational conditions, prediction accuracy, and optimisation were interrelated. The simulated results illustrate the progressive decrease of net power, thermal efficiency, and exergy efficiency with increasing twist ratios and at a same time, the decrease in pressure drop, indicating trade-off between increasing heat transfer and resistance to flow. These nonlinear trends were well represented by the Deep Learning model, indicating that it is a reliable model in predicting the performance of ORC when considering extremely high R2 and low MAE/RMSE among all the meaningful parameters. Furthermore, the model serves to define conditions that can optimise net power and Nusselt number at the sacrifice of allowable friction losses; and the results from the optimisation show large increases in power production and heat transfer. In saying this, the combined simulation-prediction-optimisation system is a valuable means of enhancing performance of an ORC system overall.

The practical applicability of the proposed ORC framework in real-world low-temperature waste heat recovery systems such as industrial exhaust recovery, geothermal energy conversion, and heat recovery from manufacturing processes. The improved thermal performance and higher net power output achieved through twisted tape enhancement can contribute to reduced energy consumption and improved operational efficiency in compact heat exchanger systems. From an engineering perspective, the reduction in pressure losses while maintaining enhanced heat transfer provides important design advantages for evaporator sizing, pumping power reduction, and long-term system reliability. Furthermore, the integration of the DNN-based prediction framework enables rapid performance estimation and adaptive operational control, which can support intelligent thermal management and real-time optimisation in future industrial ORC installations.

6. Conclusion

This paper discusses an integrated prediction and optimization framework based on DNN which can predict and optimize the operation of Organic Rankine Cycle systems with accurate results and improved performance. The results indicate the model is able to describe nonlinear thermodynamic behaviour with R2 values greater than 0.98, and with a low error level in all key parameters. Part of the operating parameters that were identified during the optimisation stage and strongly enhance the system outputs are the high Nusselt number of 769.108, the high net power generation of 4.672 kW, and the improved thermal and exergy efficiencies of 6.961% and 25.160, respectively. These results substantiate the notion that the combination of deep learning and thermodynamic studies can be used to inform the design of ORC and operational decision-making. The proposed architecture provides its training data, however, only during the simulation cases, which cannot be deemed as an accurate representation of the uncertainties or dynamic changes in the real ORC installations. Real-time operational data and experimental data can be used in future studies to enhance the generalizability and robustness of the model.

Future Work

Future research will be concentrated on the experimentation of ORC systems with twisted tapes as a method of validation for the suggested framework. Moreover, the application of live data for the purpose of coefficient tuning and performance enhancement in various operating scenarios will also be explored.

Declarations

Funding

There is no specific funding to support this research.

Conflict of Interest

The authors declare that they have no conflicts of interest regarding this work.

Data Availability

The data that support the findings of this study are not publicly available due to confidentiality agreements but are available from the corresponding author upon reasonable request.

Code Availability

Not applicable.

Author Contributions

Zhao Jiayue, contributed to the design and methodology of this study, the assessment of the outcomes, and the writing of the manuscript.

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