ACKNOWLEDGMENT

In our effort towards the realization of this project work, we have drawn on the guidance of many people for which we are glad to acknowledge. With profound sense of gratitude and regards we convey our sincere thanks to our internal guide Prof. Swapnil Ramani, Asst. Professor, Department of Mechanical Engineering, Don Bosco College of Engineering for his esteemed suggestions, sincere efforts and inspirations given to us in completing this project work. We would also like to thank Prof. Ramnath Prabhu Bam, lecturer Mechanical Engineering Fr Agnel Polytechnic-Verna for their valuable advice, help, guidance and continuous support given to us in completing our project work. We would also like to express our heartfelt thanks to Dr. Pravin Verekar, Head of Department of Mechanical Engineering, Don Bosco College of Engineering for his valuable advice, encouragement, help, guidance, and writing support throughout the development of this project. We are thankful to Dr. Neena Panandikar, Principal, Don Bosco College of Engineering, Fatorda for permitting us to carry to our project. We express our deep gratitude to this institute, Don Bosco College of Engineering, which provided an opportunity and platform for fulfilling our dreams and desire to reach our goal. We are also thankful to one and all to who directly or indirectly encouraged us to complete this project.

ABSTRACT

Heat exchangers are essential components in industrial processes for efficient heat transfer. Fouling is the accumulation of unwanted deposits on heat transfer surfaces which significantly impacts their performance. Timely detection of fouling is crucial to prevent loss of energy, low efficiency, and potential equipment failure. In this project, we propose a novel approach for the detection of fouling in heat exchangers using machine learning techniques. We have collected data from various sensors monitoring temperature, pressure, flow rate, and other relevant parameters. By training machine learning algorithms on this dataset, we have developed predictive models capable of identifying fouling patterns and predicting fouling levels. Our experimental results demonstrate the effectiveness of the proposed approach, achieving high accuracy in fouling detection. Furthermore, we have investigated the feature importance to gain insights into the underlying factors contributing to fouling. This research provides valuable insights into the application of machine learning for predictive maintenance in heat exchangers, enabling proactive measures to reduce fouling, optimize performance, and enhance energy efficiency. The proposed methodology holds significant potential for real-world implementation, offering a cost-effective and reliable solution for fouling detection in heat exchangers across various industries.

CONTENTS

List of Figures

NOMENCLATURE

R_f	fouling factor
N_u	Nusselt number
Re	Reynolds number
Pr	Prandtl number
$Q^{\cdot}$	thermal power
h_t	tube side heat transfer coefficient
h_s	shell side heat transfer coefficient
Rf	total thermal resistance of fouling
U_c	overall HTC in clean condition
U_f	overall HTC in fouled condition
R_w	thermal resistance of tube wall

CHAPTER 1

INTRODUCTION

Heat exchangers play a crucial role in many industrial processes, as they are used to transfer heat between fluids or between a fluid and a solid surface. These devices can be found in a wide range of applications, including power plants, chemical processing plants, refrigeration systems, and many others. Various studies have been carried out to study, analyze, and predict its performance. One of major phenomenon that limits heat exchanger performance is attributed to fouling. Fouling in heat exchangers refers to the accumulation of unwanted deposits or substances on the heat transfer surfaces, which reduces the heat transfer efficiency of the exchanger. Fouling can occur in various types of heat exchangers, including shell-and-tube, plate-and-frame, and finned tube exchangers. Scales, sediment, corrosion byproducts, biological growth, or organic materials can all be examples of fouling deposits. As insulating layers, these deposits slow down the rate at which heat is transferred between the two fluids moving through the exchanger. In order to maintain the desired heat transfer, the heat exchanger must work harder and use more energy. Based on this, various studies and approaches have focused on reduction, elimination of fouling. One important aspect of maintaining heat exchanger is predictive maintenance. Predictive maintenance involves the use of various techniques to monitor the condition of equipment and predict when maintenance is required. By using predictive maintenance techniques, companies can avoid costly unplanned downtime and extend the lifespan of their equipment.

1.1 Types of heat exchangers

1.1.1 Shell and tube heat exchanger

A shell and tube heat exchanger is a form of heat exchanger that has a number of tubes inside of the shell, which is a sizable exterior vessel. It is frequently used to transmit heat between two fluids without the fluids coming into direct contact with one another, such as a hot fluid and a cold fluid.

The following elements make up the shell and tube heat exchangers fundamental design:

1. Shell: The fluid that needs to be heated or cooled is contained inside the shell, which is a cylindrical vessel. It often consists of metal, such as carbon steel or stainless steel, and contains ports for the fluids entry and outflow.

2. Tubes: Inside the shell, the tubes are a bundle of pipes with a tiny diameter. They might be U- shaped or straight. Through these tubes, the fluid that needs to exchange heat travels. Depending on the use and the characteristics of the fluids involved, the tubes are frequently constructed from materials like titanium, stainless steel, or copper.

3. Tube Sheets: At each end of the shell and tube heat exchanger are metal plates known as tube sheets. In order to prevent fluid mixing, they seal off the shell and tube sides and support the tubes.

4. Baffles: Placed inside the shell to guide fluid flow and improve heat transfer efficiency, baffles are plates or other structures. They increase turbulence and block the fluids bypass.

5. Spaces outside and inside the tubes are referred to as the shell side and tube side, respectively. Typically, the cold fluid surrounds the tubes in

the shell while the hot fluid flows through the tubes (tube side). Heat is effectively transferred through the tube walls thanks to this configuration.

Whereas the opposite fluid (the shell side) circulates through the tubes. Through the tube walls, heat is transmitted from one fluid to another. A shell and tube heat exchangers design and configuration can alter depending on the needed heat transfer rate, the fluid characteristics, and the available space.

Many different industries, including power generation, chemical processing, petroleum refining, HVAC (heating, ventilation, and air conditioning), and many more, use shell and tube heat exchangers extensively. Their durability, high heat transfer efficiency, and adaptability to a variety of fluids and temperature changes make them popular.

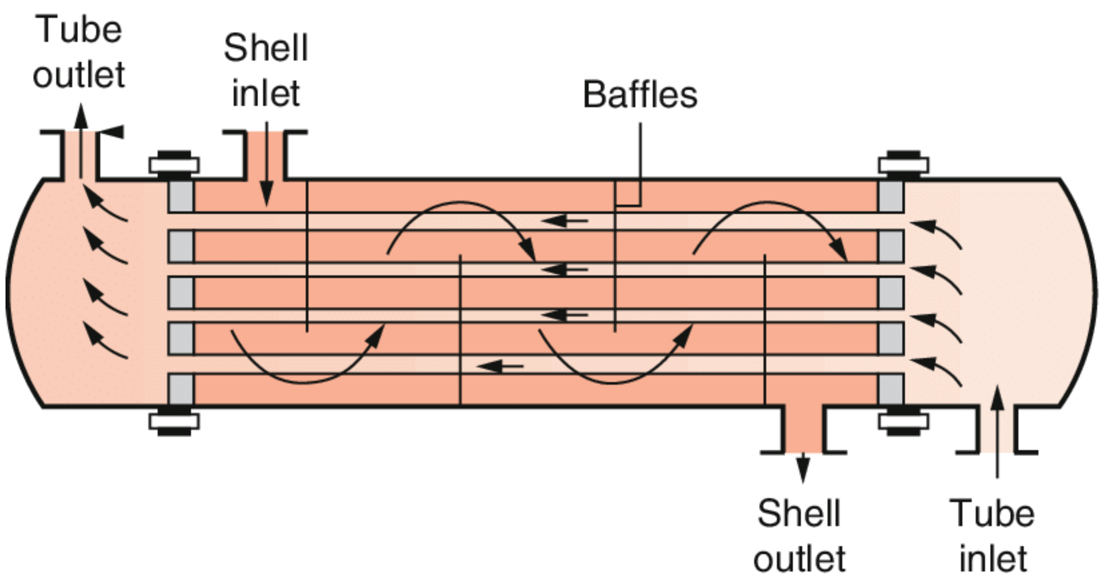

Figure 1.1: Shell and tube heat exchanger

1.1.2 Plate heat exchanger

Another popular type of heat exchanger for transmitting heat between two fluids is a plate heat exchanger. In contrast to shell and tube heat exchangers, plate heat exchangers transmit heat through a network of metal plates.

The following elements are used in a plate heat exchangers design:

1. Plates: A succession of thin metal plates, often made of titanium or stainless steel, are used to transmit heat. These plates contain precisely crafted corrugations or patterns that increase the surface area for heat transmission while generating turbulent flow.

2. Frame: A frame, which offers structural support and keeps the plates aligned, is used to hold the plates together. The frame also has connectors for the two fluids intake and outlet ports.

3. Gaskets: Gaskets are positioned between the plates to form a seal and stop the two fluids from mixing. Additionally, they control fluid flow across several channels to ensure effective heat transfer.

4. Separate inlet and exit ports are provided for the two fluids in the plate heat exchanger. Hot fluid enters through one set of ports, travels through alternate channels created by the plates, and then exits through a different set of ports. In order to allow heat transfer between the two fluids, the cold fluid also travels along a similar path but through different channels.

The two fluids move in opposition to one another as the plates are in use. Through the plate walls, heat is transmitted from one fluid to another. The plates corrugated structure encourages turbulent flow and improves heat transfer efficiency. The numerous plates; broad surfaces enable efficient heat exchange with a small physical footprint.

In many different applications, such as HVAC systems, refrigeration, food and beverage processing, chemical processing, and many more, plate heat exchangers are frequently utilised. High heat transfer rates, compact size, fluid handling versatility, ease of maintenance, and the capacity to withstand high pressures and temperatures are just a few of their benefits. Additionally, because of their modular architecture, the heat exchanger system may be easily expanded or modified to meet changing heat transfer requirements.

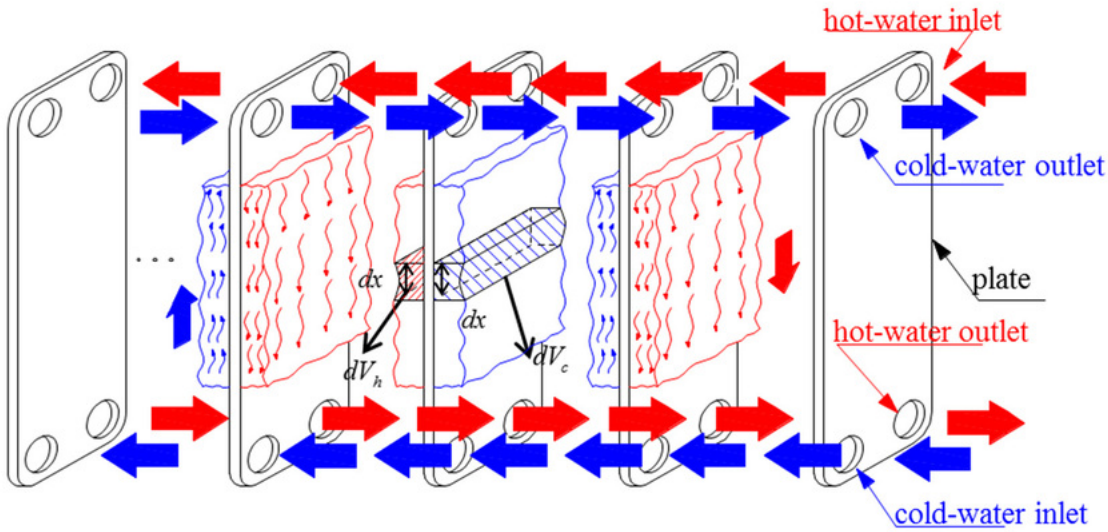

Figure 1.2: Plate heat exchanger

1.1.3 Finned heat exchanger

In order to enhance the heat transfer surface area and boost heat transfer efficiency, a finned heat exchanger, often referred to as a finned tube heat exchanger, uses expanded surfaces. Thin metal sheets or plates called fins are fastened to the outside of heat transmission tubes.

A finned heat exchangers design typically contains the following elements:

1. Tubes: The principal heat transmission surface is the tube. They could be internally strengthened tubes or plain tubes. When the fluid flow rate is high and fouling is not an issue, smooth tubes are frequently employed. To improve heat transfer, internally improved tubes include ridges or grooves on the inner surface.

2. Fins: Thin metal sheets or plates, mounted to the outside of the tubes, are known as fins. They help improve the total heat transfer rate and expand the surface area accessible for heat transfer. Materials with a high thermal conductivity, such copper or aluminium, are frequently used to create fins.

3. Fins Configuration: Depending on the application and necessary heat

transmission, fins can be organized in a variety of ways. Plain fins, which are straight fins with no further surface changes, serrated fins, which have serrations running the length of them to increase heat transfer, and louvred fins, which have alternate slit-like holes to improve airflow and heat transfer, are common fin configurations.

4. Air Flow: Air is frequently employed as the secondary fluid for heat transfer in finned heat exchangers. The fluid inside the tubes and the air around them may exchange heat more easily thanks to the fins. Fans or blowers can help to improve air movement, which is necessary for effective heat transfer.

In situations where one fluid, such as a liquid or gas, needs to be cooled or heated by exchanging heat with another fluid, typically air, finned heat exchangers are frequently utilised. They are frequently used in industrial processes, automobile radiators, HVAC systems, refrigeration, air conditioning, and other applications where limited space or faster heat transfer rates are crucial.

The surface area accessible for heat transfer is greatly increased by the addition of fins, which leads to increased heat transfer efficiency and smaller equipment. Finned heat exchanger design and selection are influenced by a variety of elements, including space constraints, fluid characteristics, operating circumstances, and heat transfer needs.

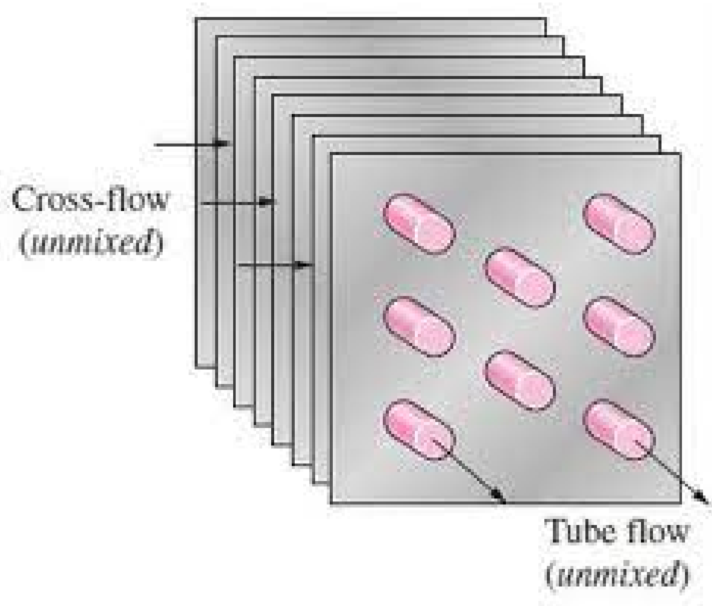

Figure 1.3: Finned heat exchanger

1.1.4 Double pipe heat exchanger

A simple sort of heat exchanger that consists of two concentric pipes or tubes is a double pipe heat exchanger, sometimes referred to as a hairpin heat exchanger or a tube-in-tube heat exchanger. Heat transfer between the hot and cold fluids is made possible by their independent pipe flows.

The following elements are commonly included in a double pipe heat exchangers design:

1. Inner Tube: The inner tube, which often has a smaller diameter, transports the heated fluid. It can form a hairpin arrangement by being straight or U-shaped. Based on the characteristics of the hot fluid and the necessary corrosion resistance, the inner tubes material is selected.

2. Outer Tube: The outer tube transports the cold fluid and encloses the inner tube. It functions as the heat exchangers outer shell and has a bigger diameter. The outer tubes material is often chosen for its mechanical strength and ability to withstand the cold fluid.

3. Tube Support: Along the length of the outer tube, spacers or supports are positioned at regular intervals to support the inner tube. These supports guarantee structural stability and maintain the distance between the inner and outer tubes.

4. Inlet and Outlet Ports: The heat exchanger has separate inlet and outlet ports for the hot and cold fluids. Depending on the required heat, the fluid flow can be either parallel or counterflow.

The colder fluid passing through the outer tube receives heat from the hot fluid flowing through the inner tube during operation. The tube walls, which serve as the heat transfer surface, allow heat to be transferred. The compact form of the double pipe layout makes it ideal for applications requiring low to moderate heat transmission.

Double pipe heat exchangers are frequently employed in a wide range of applications, such as small-scale process industries, laboratory uses, pilot plants, and low flow rate heat transfer applications. They are inexpensive and simple to maintain because to their relatively straightforward design and construction. In contrast to more intricate heat exchanger designs, like shell and tube or plate heat exchangers, they could have a lower heat transfer efficiency.

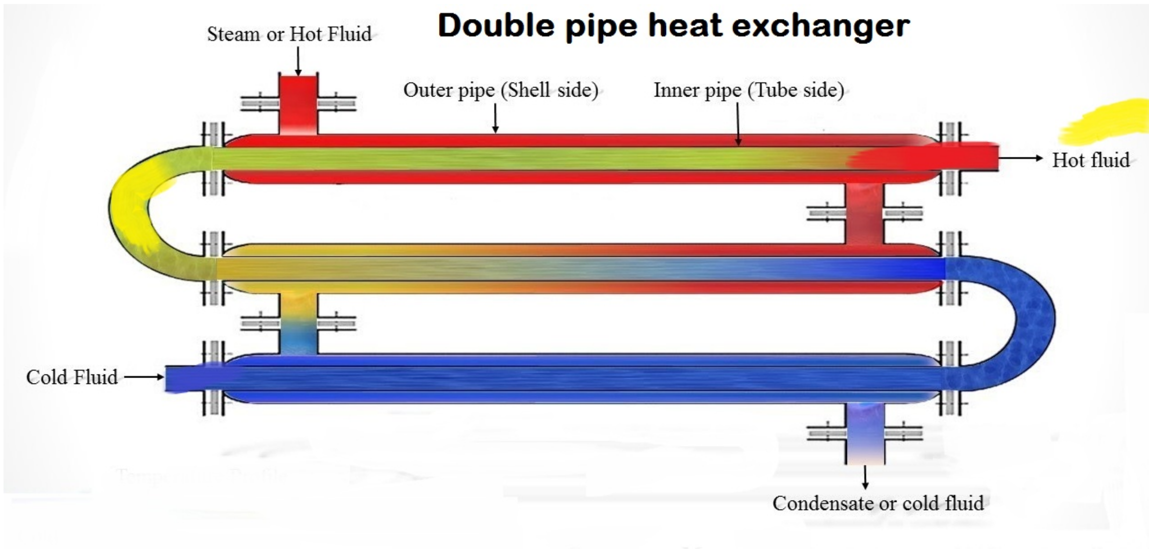

Figure 1.4: Double pipe heat exchanger

1.2 Types of fouling

There are several types of fouling that can occur in heat exchangers. The specific type of fouling depends on the nature of the fluids being processed and the operating conditions. The main types of fouling in heat exchangers include:

1.2.1 Scaling

When dissolved minerals in a fluid precipitate and create dense deposits on heat transfer surfaces, scaling takes place. Calcium carbonate, calcium sulphate, and silica are typical minerals that cause scaling. When certain minerals are present in large quantities in the fluid and when temperature or pressure conditions favour their precipitation, scaling is more likely to happen.

1.2.2 Corrosion fouling

Corrosion fouling is the term for the buildup of deposits as a result of chemical reactions between the fluid and the heat exchanger's substance. Rust and oxides can build up on the heat transfer surfaces as a result of corrosion, which can also result in the development of corrosion products. When the fluid is corrosive or when there is a mismatch between the fluid and the heat exchanger material, corrosion fouling is more prone to happen.

1.2.3 Biological fouling

On heat transfer surfaces, microorganisms including bacteria, algae, fungi, or other organic matter grow and assemble, causing biological fouling. These microbes can create biofilms, which serve as insulating layers and limit the effectiveness of heat transfer. Applications where the fluid is exposed to natural water sources, cooling towers, or other settings that encourage microbial development are prone to biological fouling.

1.2.4 Particulate fouling

When solid particles, such as dirt, sediment, or debris, are present in the fluid and settle on the heat transfer surfaces, this process is known as particulate fouling. These particles may be created by the fluid itself or may be added during its treatment or processing. Particulate fouling can raise pressure drop in the heat exchanger and decrease heat transfer efficiency.

1.2.5 Organic fouling

Organic fouling is the buildup of organic materials on heat transfer surfaces, such as oils, greases, hydrocarbons, or organic compounds. Leaks, spills, or the presence of organic pollutants in the fluid can all lead to organic fouling. Organic fouling may need to be removed using specialised cleaning techniques and can drastically limit heat transfer efficiency.

It is significant to remember that various fouling types are not mutually exclusive and that a heat exchanger may experience many fouling processes at once. Fouling severity is influenced by things including fluid composition, operational circumstances, flow rates, and heat exchanger design. To reduce fouling and preserve heat exchangers' optimal performance, regular inspection, monitoring, and suitable maintenance procedures are crucial.

1.3 Types of maintenance

There are several types of maintenance activities associated with heat exchangers. These maintenance activities are aimed at ensuring the optimal performance, efficiency, and longevity of the heat exchanger. The main types of maintenance for heat exchangers include:

1.3.1 Preventive maintenance

It involves scheduled and regular tasks carried out to avert any problems and guarantee the continuing operation of the heat exchanger. It involves chores including routine maintenance, cleaning, lubrication, and calibration. Preventive maintenance minimises the possibility of unexpected breakdowns and enhances the performance of the heat exchanger by assisting in the early detection and resolution of minor difficulties.

1.3.2 Predictive Maintenance

To continuously monitor the health and operation of the heat exchanger, predictive maintenance employs a number of methods and tools. In order to identify probable failures or performance degradation, sensors, data analysis, and predictive modeling are used. Predictive maintenance can spot emerging concerns and enable prompt intervention, minimising downtime, by monitoring parameters like temperature, pressure, vibration, or fluid flow. Predictive maintenance can identify emerging issues and allow for timely intervention, minimizing downtime and optimizing maintenance efforts.

1.3.3 Corrective Maintenance

known as breakdown or reactive maintenance, involves repairing or restoring the heat exchanger when it has experienced a failure or malfunction. Corrective maintenance is performed after a failure has occurred and aims to restore the heat exchanger to its normal operating condition. While reactive maintenance is not desirable, it is sometimes necessary when unexpected failures happen. However, minimizing corrective maintenance through effective preventive and predictive maintenance practices is generally preferred.

1.3.4 Shutdown Maintenance

Known as turnaround maintenance or shutdowns, entails thorough examination, upkeep, and overhaul of the heat exchanger over predetermined shutdown intervals. This kind of maintenance is normally carried out at regular intervals or whenever the heat exchanger needs major repairs or component replacements. In-depth checks, cleanings, repairs, and replacements are achievable during shutdown maintenance that might not be possible during normal operation. It guarantees the durability, functionality, and safety of the heat exchanger.

1.3.5 Cleaning and Fouling Removal

To eliminate fouling deposits and maintain optimal heat transfer efficiency, the heat exchanger must be cleaned on a regular basis. Depending on the type of fouling, many cleaning processes may be used, including mechanical brushing, chemical cleaning, high-pressure water jets, or specialised cleaning methods. Cleaning and fouling removal maintenance procedures aid in reducing the detrimental effects of fouling, cutting down on energy use, and extending heat exchanger lifespan.

For heat exchangers to function reliably, efficiently, and for a long time, each sort of maintenance is critical. In order to minimise unplanned downtime, maximise performance, and lower overall lifespan costs, a well-planned maintenance programme includes several maintenance procedures based on the particular needs of the heat exchanger and the operating environment.

1.4 Objective

- To build fouling dataset using softwares like MATLAB and ANSYS which will further help us in building an accurate model .
- To collect data acquired by the industry for both normal and faulty scenarios.
- Training model using various machine learning algorithms like classification and regression.
- To evaluate the model effectiveness in detecting and classifying different heat exchanger faults based on the collected data.
- Integrate the trained machine learning model into a real-time monitoring system for heat exchangers.
- The model should be able to analyze data from sensors installed in the actual heat exchanger system and detect faults based on the patterns and characteristics learned during the training phase.

CHAPTER 2

LITERATURE REVIEW

2.1 The water fouling development in plate heat exchangers with plates of different corrugations geometry.

Plate heat exchangers (PHEs) play a crucial role in various industries, including power generation, chemical processing, and HVAC systems. However, fouling, the accumulation of unwanted deposits on heat transfer surfaces significantly hampers their efficiency and performance. This research paper focuses on investigating water fouling development in plate heat exchangers with plates of different corrugation geometries.

The primary objective of this study was to evaluate and compare the fouling behavior of PHEs with plates of different corrugation geometries when exposed to water as the working fluid. The research aimed to provide insights into the impact of corrugation design on fouling development, which can assist in the development of more efficient heat exchangers and better fouling mitigation strategies. The experimental study was conducted using a specially designed test rig equipped with a PHE. The PHE plates, made of stainless steel, were fabricated with different corrugation geometries, including herringbone, chevron, and sine-wave patterns. The water flow rate, temperature, and pressure were controlled throughout the experiments. To investigate fouling behavior, the PHE was subjected to continuous operation under controlled conditions. The fouling development was monitored by measuring the pressure drop across the PHE and assessing the heat transfer coefficient. Additionally, fouling deposits were sampled and analyzed to determine their composition and thickness.

Moreover, the fouling growth can decrease the heat transfer efficiency, clog the heat transfer channels of the equipment, and result in severe economic losses together with increased energy consumption and the consequent rise of the carbon footprint. The fouling in industrial equipment can be caused by several mechanisms, namely crystallization, particulate, chemical reaction, corrosion, and biological. Its development in time is sequential and can be regarded as follows:

1. Initiation period, when an initial layer is created, can be characterized by convective transport and deposition of fouling precursors.
2. Diffusion transport of fouling particles from the fluid bulk to the surface; further attachment of the particles to the surface, where chemical reactions and possible biological adhesion processes take place.
3. Removal of the particles caused by the shear stress on the wall.
4. The ageing of fouling, which is characterised by a change of created fouling layer properties.

Fouling is an intricate process, which accounts for a lot of factors, among which are the properties of the fouling fluid, velocity of the fluid flow, heat transfer coefficient, temperature of the heat transfer surface, material and geometry, etc. The solution of the developed physical-and-mathematical model, were performed using the finite difference method. The model was implemented in the Mathcad software. The results of the modeling allow estimating the change of PHEs thermal and hydraulic behavior depending on the geometry of plates. To investigate the influence of different PHE design parameters, such as corrugation inclination angle and number of plates in a heat exchanger, on its fouling behavior, the presented earlier mathematical model was applied. The modeling for developing in time of fouling thermal resistance Rf, heat loads Q and pressure drop was performed for the PHE consisting of 150 plates and 225 plates with the varying corrugation inclination angle in the range from 35○ to 65○ and the obtained results are presented further.

The performed application of the developed model shows, that the ability to correctly design the heat transfer channels geometry accounting for the fouling formation in channels can help to reduce the total cost of the equipment purchase and energy consumption during the operation. The combination of the scheduled maintenance and its cost, proper design of the PHEs with the precise geometry of the corrugated plates, will enable to decrease the energy consumption in industrial production processes, as well as increase the performance and durability of heat transfer equipment with reliable prediction at the design stage. The data for fouling thermal resistance for the PHE from 150 plates are presented and for the PHE with 225 plates. The results of modeling for medium channels with average angle βm = 50○ and from plates with βh = 65○ show that for PHEs with plates of higher angle β, the thermal resistance of fouling is much smaller and heat load much bigger than for PHE with βl = 35○. The heat load for PHE with 150 plates with the corrugation inclination angle βl = 35. For PHEs with low and medium angles βl = 35○ and βm = 50○ such an increase of heat transfer area practically does not affect the recuperated heat, and the decrease of pressure drop is only to 35 kPa. This is not making such an option better than PHE with 225 plates, counting for the additional cost involved.

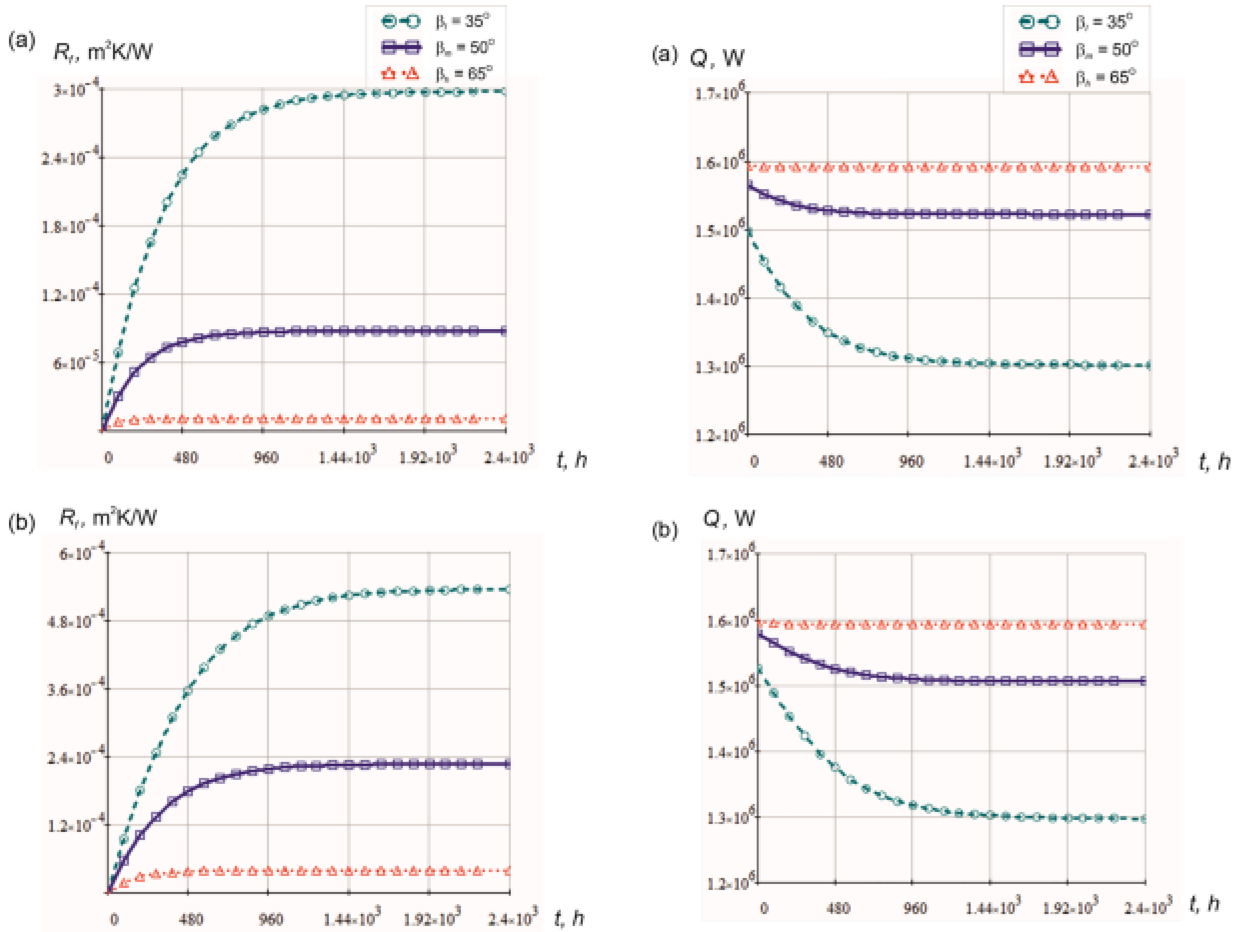

Figure 2.1: Fouling resistance and heat load develpoed in time for PHE with 150 and 225 plates

The developed mathematical model is capable to perform the analysis of PHEs performance with the fouling sediment layer on its heat transfer surface and estimating the change of the process parameters in time taking into account the influence of plate corrugations geometry. It must be accounted for the correct selection of PHE in the conditions of fouling. The implementation of an additional number of plates with identical low inclination angle β to the main flow direction in PHEs increases the fouling thermal resistance, and after some period of operation, it becomes higher than for PHEs with a lower number of plates. At the same time, a higher number of plates promote the decrease of pressure drop in PHE. The implementation of an additional number of plates with identical low inclination angle β to the main flow direction in PHEs increases the fouling thermal resistance, and after some period of operation, it becomes higher than for PHEs with a lower number of plates. At the same time, a higher number of plates promote the decrease of pressure drop in PHE.

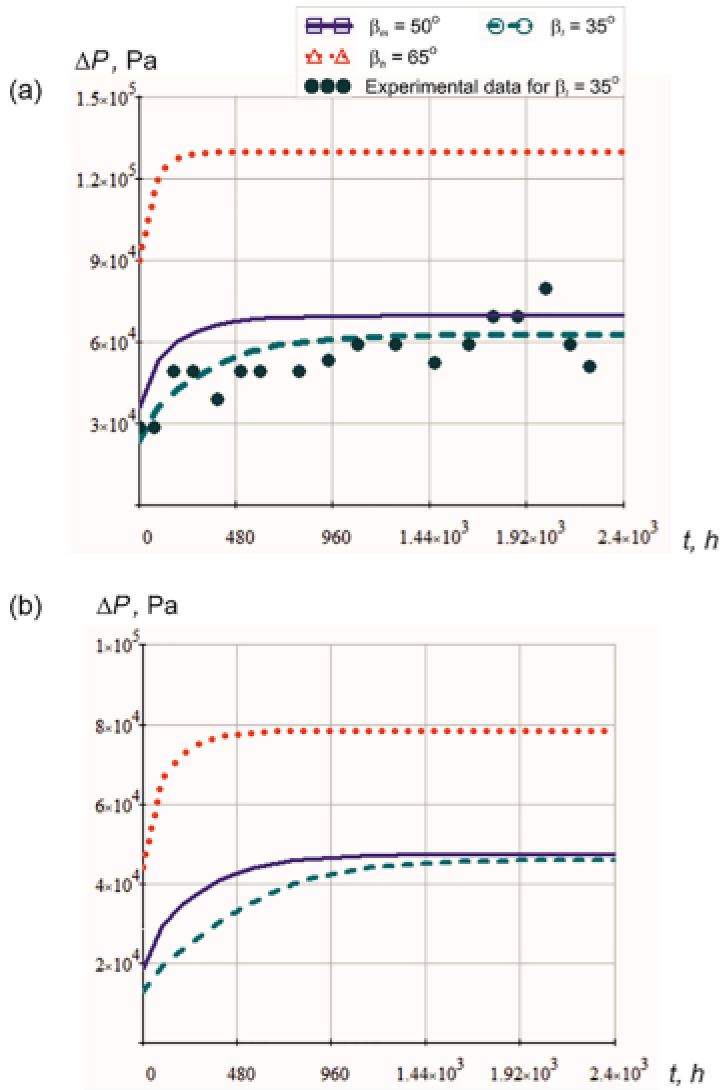

Figure 2.2: Pressure drop change in time for PHE with 150 and 225 plates

The PHE design with the higher inclination angle β shows a smaller increase of pressure drop than the design for the lower inclination angle β at the same conditions. With higher values of pressure drop at the start of the operation, in time can lead to the same or even smaller magnitude of pressure losses. While the quantity of the recuperated heat can be significantly larger.[1]

2.2 Estimation of thermal effects of fouling growth for application in the scheduling of heat exchangers

In various industries such as oil , pulp , sugar, diary and other process plants , several heat exchangers are used which maybe impaired by fouling build up in heat Transfer surfaces of the exchangers, while during this process monitoring of fouling becomes essential in order to collect the data for scheduling and to perform heat exchanger cleaning if needed for the elimination of adverse effects of fouling. Hence three different methods are developed to conduct the monitoring of fouling in heat exchangers.

Method 1

This method consist of widely known mathematical relationships in absence of fouling

R_w – thermal resistance of tube wall

h_t – tube side heat transfer coefficient

h_s – shell side heat transfer coefficient

U_c – overall HTC in clean condition

U_f – overall HTC in fouled condition

R_f – fouling factor

$U_c = \frac{1}{\frac{1}{h_t}+R_w+\frac{1}{h_s}}, U_f = \frac{1}{\frac{1}{h_t}+R_w+\frac{1}{h_s}+R_f}$

Finally calculate

$R_f = \frac{1}{U_f} - \frac{1}{Uc}$

Rf– total thermal resistance of fouling is expressing the combined fouling effect on both tube and shell side of tube wall.

Method 2

This method uses the similar but short cut approach as Method one which is widely used in the industry .

Method 3

This method uses Nusselt’s equation to determine time characteristics of the thermal resistance of fouling for a specific period of exchanger operation, unexpected sharp changes.

$N_u = C.Re^a.Pr^b.(Pr_t/Pr_{tw})^o$

N_u – Nusselt number

Pr – Prandtl number

$Q^{\cdot}$ – thermal power or heating duty, W

Re – Reynolds number

Rf – total thermal resistance of fouling, m2 **.**K/W

where C, a, b, o – constants.

Method 3 is employed here for more reliable calculation of the thermal resistance of fouling, usually resulting in time characteristics that appear more credible than those generated by method 1 and method 2, thereby the studies show that after evaluating the above 3 methods , method 3 gives the best positive results whereas method 1 indicated unrealistically large jumps in the values of fouling resistance.[2]

2.3 Characteristics of fouling development in shell and tube heat exchnager: Effects of velocity and installation location

Hydrodynamic effects such as flow velocity and shear stress at the surface, influence fouling. Within the pressure drop considerations the higher the velocity, higher will be the fouling. While the Uniform and constant flow of heat exchangers causes less fouling. Foulants suspended in the process fluids will deposit in low velocity regions .Maintain relatively uniform velocity across the heat exchanger to reduce the incidence of sedimentation an accumulation of deposits fouling decreases at higher fluid velocities because increasing flow velocity increases the fluid shear stress, which causes more removal of deposits when the heat exchanger was installed at the suction inlet of pump, suggesting that installing the heat exchanger at the suction-inlet of the pump could cause more fouling deposition as compared to the Shoot outlet.[3]

2.4 Fouling and Its Effects on Air-cooled Condensers in Split System Air Conditioners (RP-1705)

Air-side fouling of condensers on small air conditioning systems such as split systems and rooftop units has always been considered a significant problem. Since most of these systems have a fixed speed condenser fan, the fouling reduces airflow by imposing flow resistance. Reducing airflow and potentially increasing the resistance to heat transfer on the heat exchanger's surface are assumed to reduce the total capacity of the condenser, which, in turn, degrades the capacity and efficiency of the entire cycle. As a result, they have conducted laboratory tests of field samples of condensers collected from air conditioners. These results facilitate the first evidence-based guidance on coil maintenance, performance degradation, design, and diagnostics. Based on the results, in most of the cases, fouling does not have a significant effect on coil's heat transfer capacity, hence system efficiency, even though it significantly decreases the coil's airside pressure drop.[4]

2.5 Monitoring fouling in heat exchangers under temperature control based on excess thermal and hydraulic loads

Fouling affects heat exchanger's performance leading to additional utility requirements and economic penalties. Performance monitoring is required to ensure that exchangers operate within allowable limits. Fouling decreases the cross-sectional areas for the fluids to pass through and increases the pressure drop. These result in an overall reduction in thermal and hydraulic performance. Continuous monitoring of overall heat transfer rate and pressure drop can be used to detect the onset of such performance degradation and help to trigger maintenance. The ratio of excess pressure drop over that in the clean state is used as the hydraulic performance indicator. Similarly, the ratio of excess thermal load due to additional utility consumption over that in the clean condition is used as a thermal performance indicator. The results show that the time to approach the thermal and hydraulic performance limits is dependent upon the magnitude of process flow rates, set points and the fouling side. As the process flow rate increases, the duration of healthy operation reduces due to the higher fouling rates. Similarly, the period of healthy operation is also reduced if the required overall heat transfer rate increases due to changes in the set point. This work assumes an asymptotic fouling rate, which is commonly observed in the process industries.[5]

2.6 Modelling of fouling in a Plate heat exchanger with high temperature pasteurization process

This research paper explores the fouling phenomenon in plate heat exchangers used in high-temperature pasteurization processes. The paper aims to develop a mathematical model to predict and analyse fouling effects, thereby assisting in the optimization and maintenance of plate heat exchangers.

The primary objective of this research is to develop a reliable mathematical model for predicting fouling behaviour in a plate heat exchanger during high-temperature pasteurization processes. By understanding fouling mechanisms and their impact on heat transfer efficiency, the aim is to optimize the process and reducing maintenance costs.

The research employs a combination of experimental investigations and mathematical modelling. Initially, experiments are conducted using a plate heat exchanger under controlled conditions to measure temperature profiles, pressure drops, and fouling tendencies. The experimental data are then used to validate the developed mathematical model. The mathematical model takes into account various factors, such as fluid properties, heat transfer coefficients, flow velocities, and fouling resistance.

The research paper presents the results obtained from the experimental investigations as well as the mathematical model simulations. The theoretical response is obtained by simulating the plant model using MATLAB and SIMULINK software. The mathematical models are validated against the data collected from the plant. Comparison is done with the predicted fouling behaviour with the experimental data, demonstrating the models effectiveness in capturing the fouling trends accurately.

The findings reveal the significance of fouling on heat transfer efficiency and pressure drop across the plate heat exchanger. The study highlights the importance of regular maintenance and cleaning to mitigate fouling effects and enhance operational performance.

The research paper provides valuable insights into the fouling behaviour of plate heat exchangers used in high-temperature pasteurization processes. The developed mathematical model offers a useful tool for predicting and understanding fouling phenomena, allowing for optimization and maintenance planning to improve heat transfer efficiency and minimize costs.

The findings of this study contribute to the field of heat exchanger design and operation, especially in the context of high-temperature pasteurization processes. Further research and development based on this study could lead to enhanced performance and reliability of plate heat exchangers in industrial applications.[6]

2.7 Experimental investigation of convective heat transfer from sewage heat exchange pipes and the construction of a fouling resistance based mathematical model

This research paper focuses on studying convective heat transfer in sewage heat exchange pipes. This paper aims to experimentally investigate the heat transfer process and develop a mathematical model that considers fouling resistance for more accurate predictions and improved design of heat exchange systems. The primary objective of this research is to investigate the convective heat transfer characteristics of sewage heat exchange pipes and develop a mathematical model that incorporates fouling resistance effects.

This research utilizes a combination of experimental investigations and mathematical modelling. Experimental tests are conducted using a dedicated setup to measure the convective heat transfer coefficients and analyse the fouling behaviour in sewage heat exchange pipes. The authors consider various factors, including fluid properties, flow velocities, temperature differentials, and pipe geometries, to accurately capture the convective heat transfer process. Based on the experimental data, a mathematical model is developed that incorporates fouling resistance. The model takes into account factors such as fouling thickness, fouling resistance, and their impact on convective heat transfer performance. The model is validated against the experimental results to assess its accuracy and predictive capability.

This research paper presents the experimental results obtained from the investigation of convective heat transfer in sewage heat exchange pipes. The authors analyse the heat transfer coefficients, pressure drops, and fouling tendencies under different operating conditions. The findings demonstrate the significant impact of fouling on convective heat transfer and highlight the need for accurate modelling to optimize system performance. The aim of the test system was to verify the thermal balance and reliability of the test system. The test system consists of shell and tube type heat exchanger due to its high heat transfer efficiency. The heat flux is made constant by using heat tapes heating.

The mathematical model developed in this study successfully incorporates fouling resistance effects and provides accurate predictions of the convective heat transfer performance in sewage heat exchange pipes. The model shows that fouling resistance is distributed asymptotically and asymptotic time is inversely proportional to square of the initial flow velocity and asymptotic values are linear and has decreasing relationship with initial flow velocity. The models effectiveness is confirmed by comparing the model predictions with the experimental data, showing good agreement. The research paper by

Jialin Song, Zhibin Liu, Zhongjiao Ma, and Jili Zhang contributes to the understanding of convective heat transfer in sewage heat exchange pipes. The experimental investigations and the construction of a fouling resistance-based mathematical model provide valuable insights into the fouling phenomenon and its impact on heat transfer efficiency.

The findings emphasize the importance of considering fouling resistance in the design and operation of sewage heat exchange systems. The developed mathematical model offers a tool for accurate prediction and optimization of heat transfer performance, aiding in the efficient design and maintenance planning of such systems. Overall, the research paper provides valuable contributions to the field of convective heat transfer in sewage heat exchange pipes. Further research based on this study could lead to improved heat transfer efficiency, energy savings, and better management of fouling-related challenges in sewage heat exchange systems.[7]

2.8 Application of feed forward neural network for fouling thickness estimation in low density polyethylene tubular reactor

This research focuses on estimating fouling thickness in a Low-Density Polyethylene (LDPE) tubular reactor using a Feed Forward Neural Network (FFNN) with Levenberg-Marquardt training. The LDPE polymerization process in the tubular reactor is prone to fouling due to its exothermic nature and heating-cooling requirements.

To develop the FFNN model, a dataset is generated by combining simulations of the LDPE tubular reactor using Aspen Dynamic and the fouling build-up equation. The tubular reactor is modeled under steady-state conditions, incorporating a kinetic model and relevant parameters. The formulation for fouling thickness is also integrated into the model.

The chosen FFNN structure is based on the perceptron topology. This topology introduces adjustable weight parameters that optimize the networks performance during the learning process. By training the FFNN model with the above training method, the researchers aim to accurately predict fouling thickness in the cooling zone of the LDPE tubular reactor. The model learns from the generated fouling data and generalizes its predictions to unseen cases.

The research demonstrates the practical application of FFNN modeling with Levenberg-Marquardt training for estimating fouling thickness in an LDPE tubular reactor. Accurate prediction of fouling thickness enables effective control and management strategies to address fouling-related challenges in the LDPE polymerization process.[8]

2.9 Novel And Robust machine learning approach for estimating the fouling factor in heat exchangers

The research focuses on developing a robust machine learning approach to estimate the fouling factor (Rf) in heat exchangers. The fouling factor quantifies the fouling on heat transfer efficiency. The study analyzed 11,626 real-world samples to devise an accurate methodology for calculating fouling in heat exchangers.

Three novel approaches, including Gaussian Process Regression, Decision Trees, and Bagged Trees, were used alongside traditional techniques like Support Vector Regression and Linear Regression to estimate the fouling factor. These methods leverage machine learning algorithms to improve accuracy.

Various computational methods were explored to measure fouling, including physical measurements like weight monitoring, flow rates, temperatures, overall heat transfer coefficient, and wall shear stress. Alternative approaches like electrical, photo-thermal, acoustic, and optical signals were also investigated.

By leveraging a dataset of 11,626 samples and advanced machine learning techniques, the researchers aimed to develop a robust methodology for accurately estimating the fouling factor in heat exchangers. Comparing the novel approaches with traditional techniques would determine their effectiveness and potential superiority. Ultimately, this research contributes to the development of more efficient heat exchanger systems by enabling better monitoring and management of fouling effects.[9]

CHAPTER 3

MACHINE LEARNING

Machine learning is the field of study that gives computers the ability to learn without being explicitly programmed. However, there is no universally accepted definition for machine learning. Machine learning is programming computers to optimize a performance criterion using example data or past experience. We have a model defined up to some parameters, and learning is the execution of a computer program to optimize the parameters of the model using the training data or past experience. The model may be predictive to make predictions in the future, or descriptive to gain knowledge from data.

Machine learning investigates how computers can learn (or improve their performance) based on data. A main research area is for computer programs to automatically learn to recognize complex patterns and make intelligent decisions based on data. For example, a typical machine learning problem is to program a computer so that it can automatically recognize handwritten postal codes on mail after learning from a set of examples. Machine learning is a fast-growing discipline. Here, we illustrate classic problems in machine learning that are highly related to data mining.

Machine learning is a subfield of artificial intelligence that involves the development of algorithms and statistical models that enable computers to improve their performance in tasks through experience. These algorithms and models are designed to learn from data and make predictions or decisions without explicit instructions. There are several types of machine learning, including supervised learning, unsupervised learning, and reinforcement learning. Supervised learning involves training a model on labelled data, while unsupervised learning involves training a model on unlabelled data.

Reinforcement learning involves training a model through trial and error. Machine learning is used in a wide variety of applications, including image and speech recognition, natural language processing, and recommender systems.

Steps Involved

1. Data Cleaning (to remove noise and inconsistent data)
2. Date Integration (where multiple data sources may be combined)
3. Data Selection (where data relevant to the analysis task are retrieved)
4. Data Transformation (where data are transformed and consolidated into forms appropriate for mining by performing summary or aggregation operations)
5. Data Mining (an essential process where intelligent methods are applied to extract data patterns)
6. Pattern Evaluation (to identify the truly interesting patterns representing knowledge)
7. Knowledge Presentation (where visualization and knowledge representation techniques are used to present mined knowledge to users)

3.1 Classification of Machine Learning

Machine learning implementations are classified into following categories categories, depending on the nature of the learning signal or response available to a learning system which are as follows:

3.1.1 Supervised Learning

Supervised learning is the types of machine learning in which machines are trained using well labelled training data, and on basis of that data, machines predict the output. The labelled data means some input data is already tagged with the correct output. In supervised learning, the training data provided to the machines work as the supervisor that teaches the machines to predict the output correctly. It applies the same concept as a student learns in the supervision of the teacher. Supervised learning is basically a synonym for classification. The supervision in the learning comes from the labelled examples in the training data set. For example, in the postal code recognition problem, a set of handwritten postal code images and their corresponding machine-readable translations are used as the training examples, which supervise the learning of the classification model. Supervised learning is a process of providing input data as well as correct output data to the machine learning model. The aim of a supervised learning algorithm is to find a mapping function to map the input variable(x) with the output variable(y).

3.1.1.1 Working

In supervised learning, models are trained using labelled dataset, where the model learns about each type of data. Once the training process is completed, the model is tested on the basis of test data (a subset of the training set), and then it predicts the output.

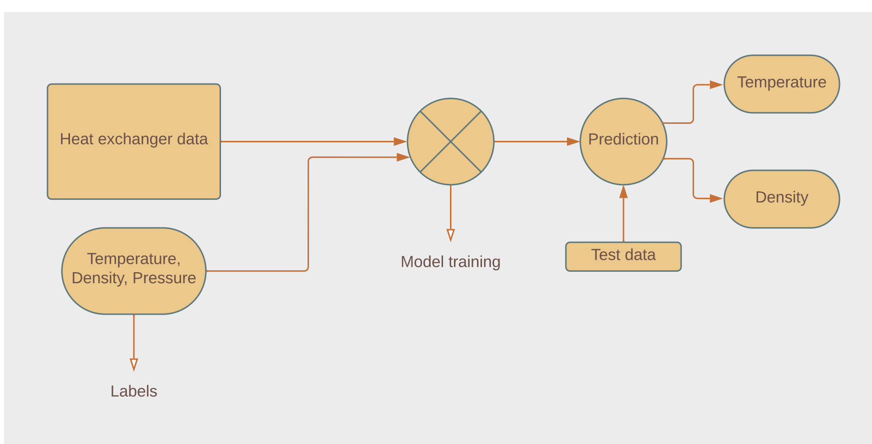

Figure 3.1: Supervised learning model

3.1.1.2 Steps involved

- First Determine the type of training dataset
- Collect/Gather the labelled training data.
- Split the training dataset into training dataset, test dataset, and validation dataset.
- Determine the input features of the training dataset, which should have enough knowledge so that the model can accurately predict the output.
- Determine the suitable algorithm for the model, such as support vector machine, decision tree, etc.
- Execute the algorithm on the training dataset. Sometimes we need validation sets as the control parameters, which are the subset of training datasets.
- Evaluate the accuracy of the model by providing the test set. If the model predicts the correct output, which means our model is accurate.

3.1.1.3 Types of supervised learning

1. Regression

Regression algorithms are used if there is a relationship between the input variable and the output variable. It is used for the prediction of continuous variables, such as Weather forecasting, Market Trends, etc. Below are some popular Regression algorithms which come under supervised learning:

- Linear Regression
- Regression Trees
- Non-Linear Regression

- Bayesian Linear Regression
- Polynomial Regression

2. Classification

Classification algorithms are used when the output variable is categorical, which means there are two classes such as Yes-No, Male-Female, True-false, etc.

- Random Forest
- Decision Tree
- Logistic Regression
- Support Vector Machine

Advantages of Supervised Learning

- With the help of supervised learning, the model can predict the output on the basis of prior experiences.
- In supervised learning, we can have an exact idea about the classes of objects.
- Supervised learning model helps us to solve various real-world problems such as fraud detection, spam filtering, etc.

Disadvantages of Supervised Learning

- Supervised learning models are not suitable for handling the complex tasks.
- Supervised learning cannot predict the correct output if the test data is different from the training dataset.
- Training required lots of computation times.
- In supervised learning, we need enough knowledge about the classes of object.

3.1.2 Unsupervised Learning

Unsupervised learning is a machine learning technique in which models are not supervised using training dataset. Instead, models itself find the hidden patterns and insights from the given data. It can be compared to learning which takes place in the human brain while learning new things. Unsupervised learning is a type of machine learning in which models are trained using unlabeled dataset and are allowed to act on that data without any supervision.

Unsupervised learning cannot be directly applied to a regression or classification problem because unlike supervised learning, we have the input data but no corresponding output data. The goal of unsupervised learning is to find the underlying structure of dataset, group that data according to similarities, and represent that dataset in a compressed format.

3.1.2.1 Working of Unsupervised Learning

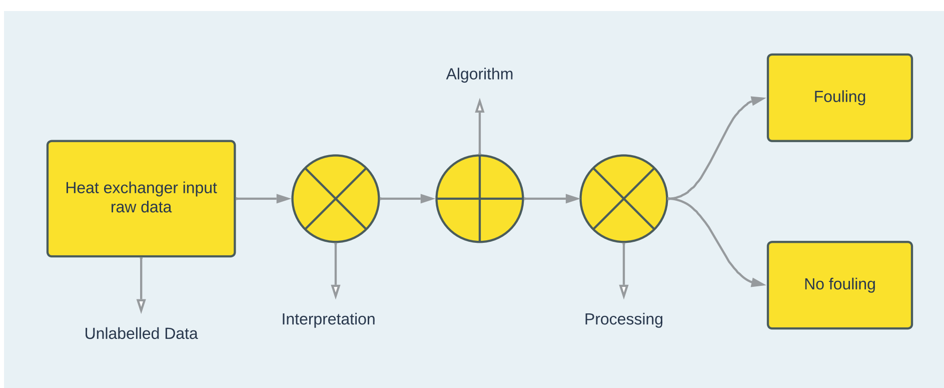

Figure 3.2: Working of Unsupervised learning

Here, we have taken an unlabeled input data, which means it is not categorized and corresponding outputs are also not given. Now, this unlabeled input data is fed to the machine learning model in order to train it. Firstly, it will interpret the raw data to find the hidden patterns from the data and then will apply suitable algorithms such as k-means clustering, Decision tree, etc.

Once it applies the suitable algorithm, the algorithm divides the data objects into groups according to the similarities and difference between the objects.

3.1.2.2 Types of Unsupervised Learning

1. Clustering

Clustering is a method of grouping the objects into clusters such that objects with most similarities remains into a group and has less or no similarities with the objects of another group. Cluster analysis finds the commonalities between the data objects and categorizes them as per the presence and absence of those commonalities.

2. Association

An association rule is an unsupervised learning method which is used for finding the relationships between variables in the large database. It determines the set of items that occurs together in the dataset. Association rule makes marketing strategy more effective. Such as people who buy X item (suppose a bread) are also tend to purchase Y (Butter/Jam) item. A typical example of Association rule is Market Basket Analysis.

Unsupervised Learning Algorithms

1. K means Clustering
2. KNN
3. Hierarchical Clustering
4. Neural Networks
5. Principle Component Analysis

Advantages of Unsupervised Learning

- Unsupervised learning is used for more complex tasks as compared to supervised learning because, in unsupervised learning, we don't have labelled input data.

- Unsupervised learning is preferable as it is easy to get unlabeled data in comparison to labelled data.

Disadvantages of Unsupervised Learning

- Unsupervised learning is intrinsically more difficult than supervised learning as it does not have corresponding output.
- The result of the unsupervised learning algorithm might be less accurate as input data is not labelled, and algorithms do not know the exact output in advance.

3.1.3 Semi - Supervised Learning

Semi-supervised learning is a type of machine learning that falls in between supervised and unsupervised learning. It is a method that uses a small amount of labelled data and a large amount of unlabeled data to train a model. The goal of semi-supervised learning is to learn a function that can accurately predict the output variable based on the input variables, similar to supervised learning. However, unlike supervised learning, the algorithm is trained on a dataset that contains both labelled and unlabelled data.

Semi-supervised learning allows neural networks to mimic human inductive logic and sort unknown information fast and accurately without human intervention. Any problem where you have a large amount of input data but only a few reference points available is a good thing for semi-supervised learning. A classic example is a photo album with millions of random images. Instead of manually labelling each picture, a human searching for images of people can just tag a few relevant samples from the database. Then the neural network can search the databank and find every image it believes represents a human.

CHAPTER 4

Data Preprocessing

1. Model Training: Select a suitable machine learning algorithm for classification, such as logistic regression, support vector machines (SVM), random forests, or deep learning models. Split the labeled data into training and testing sets. Train the model using the training data.

2. Model Evaluation: Evaluate the trained model's performance using the testing data. Common evaluation metrics for classification tasks include accuracy, precision, recall, and F1-score. Adjust the model parameters or try different algorithms as needed to improve performance

3. Prediction and Monitoring: Apply the trained model to new, unseen data to predict fouling in real-time or at regular intervals. Monitor the heat exchanger's operation and provide alerts or notifications when fouling is detected.

4. Continuous Improvement: As new data becomes available, periodically retrain and update the model to improve its performance and adapt to changing conditions. This iterative process ensures that the model remains effective over time.

The developed fouling resistance prediction model's generalization and ability to learn heat-exchanger's fouling flow and heat transfer physics will be demonstrated through an analysis of a local model of the network on a couple of test samples. Hence, an adequately trained model of the proposed fouling resistance prediction module can be deployed to make real-time predictions in an industrial setting with the inputs to the module obtained from various flow-rate and temperature sensors installed at the fluid inlets and outlets of the heat exchanger.

Data preprocessing is a crucial step in any machine learning project as it can have a significant impact on the accuracy and efficiency of the resulting model. In the case of detecting fouling in heat exchangers, proper data preprocessing can help to ensure that the machine learning algorithm can effectively detect patterns and anomalies in the data.

One of the first steps in data preprocessing is data cleaning, which involves removing any irrelevant, duplicate, or incomplete data. This is particularly important when dealing with large datasets, as even small amounts of noise or missing data can significantly impact the accuracy of the resulting model.

Once the data has been cleaned, it is important to normalize or standardize the data to ensure that all features are on a similar scale. This can be achieved through techniques such as z-score normalization or min-max scaling, which adjust the range of the data to a common scale. Normalization helps to ensure that no single feature dominates the analysis, leading to more accurate results.

Feature engineering is another important step in data preprocessing, which involves selecting and transforming relevant features to help the machine learning algorithm detect patterns in the data. In the case of detecting fouling in heat exchangers, features such as temperature, pressure, and flow rate may be important in detecting anomalies.

Finally, data preprocessing can also involve techniques such as dimensionality reduction, which involves reducing the number of features in the data to simplify the analysis. This can be particularly important when dealing with large datasets, as it can help to reduce computation time and improve model accuracy.

In conclusion, data preprocessing is a critical step in any machine learning project, and is particularly important in the detection of fouling in heat exchangers. By properly cleaning, normalizing, and transforming the data, machine learning algorithms can effectively detect patterns and anomalies in the data, leading to more accurate and efficient results.

4.1 Acquiring data

The first step to build a model is to acquire the datasets containing fouling which is collected from different sensors from the industry. We have used three different datasets to train a model which is acquired from Ashrae.

4.2 Importing dataset

```
In [2]: import pandas as pd

        excel_file = pd.ExcelFile('D:\Desktop Files\Multiple Datasets1.xlsx')
```

Figure 4.1: Importing dataset

4.3 Cleaning the dataset

```
In [3]: print(df.isnull().sum())
```

```
# Normalize and scale the data
df_normalized = pd.DataFrame(scaler.fit_transform(df_numeric), columns=df_numeric.columns)

# Merge the normalized and scaled data with the non-numerical columns
df_normalized = pd.concat([df.drop(df_numeric.columns, axis=1), df_normalized], axis=1)

# Display the normalized and scaled data
print(df_normalized)
```

Figure 4.2: Normalising dataset

CHAPTER 5

FEATURE SELECTION

During training of Machine learning models , various challenges are faced while dealing with high dimensionality data, where the number of features may be vast as compared to the number of testing data. In such cases where the data is redundant, we need to perform feature selection methods in order to reduce the dimensionality of dataset by identifying the essential features necessary to train the data and eliminating irrelevant and reductant features which simplifies the data and makes it easier to analyse. There are various feature selection methods however the choice of selection of methods depends on the characteristics of the data , methods such as Mutual information gain entropy , Random forest classifier, ANOVA , Decision tree and Recursive feature elimination are used in the given datasets.

5.1 ANOVA (Analysis of Variance)

ANOVA is a statistical method used to analyse the differences between groups of data. In the context of feature selection, ANOVA can be used to evaluate the significance of the differences in the means of a continuous feature across different classes or groups in a classification problem. More specifically, ANOVA can be used as a filter method for feature selection, where features are ranked based on their F-statistic values, which measure the differences in the means of the feature across the different classes. The higher the F-statistic value, the more significant the difference in the means and the more important the feature

Input

```
anova_1=anova.get_support()
```

```
anova_1=pd.Series(anova_1)
anova_1.index=X.columns
retained_features_anova_v1=[]
for i in range (len(anova_1)):
if anova_1[i]==True:
retained_features_anova_v1.append(X.columns[i])
retained_features_anova_v1
```

Output

```
['Severity',
'HWC-VLV',
'SA-TEMP',
'CHWC-DAT',
'SA-HUMD',
'RA-HUMD',
'OAD-TEMP',
'HWC-EWT']
```

5.2 Recursive Feature Elimination (RFE)

Recursive Feature Elimination (RFE) is a wrapper method for feature selection that uses a machine learning model to iteratively select features based on their importance or contribution to the model's performance. The RFE algorithm works by first fitting the machine learning model to the entire set of features and calculating the feature importance or coefficients. Then, it removes the least important feature(s) and fits the model again with the reduced set of features. This process is repeated until a predetermined number of features or a desired level of performance is reached. Since RFE uses a machine learning model as the basis for feature selection, it is considered a wrapper method. Other common wrapper methods include genetic algorithms, simulated annealing, and particle swarm optimization.

Input

```
from sklearn.feature_selection import RFE, SelectFromModel
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn import metrics
sel_rf=SelectFromModel(RandomForestClassifier(n_estimators=100))
sel_rf.fit(X_train , Y_train)
sel_rf.get_support()
selected_feat_rf=X.columns[(sel_rf.get_support())]
selected_feat_rf=list(selected_feat_rf)
selected_feat_rf
```

Output

['Severity', 'SF-DP', 'RF-DP', 'SA-HUMD', 'RA-HUMD', 'OA-TEMP']

5.3 Mutual information

Mutual information gain is a feature selection method that measures the dependency between a feature and the target variable in a classification or regression problem. It is a filter method, which means that it ranks features based on their individual relevance to the target variable without considering the interaction between features.

The mutual information between a feature X and a target variable Y can be calculated using the following formula: $I(X; Y) = H(X) - H(X|Y)$

Input

```
from sklearn.feature_selection import mutual_info_regression
mutual_info=mutual_info_regression(X_train , Y_train)
mutual_info
mutual_info=pd.Series(mutual_info)
mutual_info.index=X_train.columns
mutual_info.sort_values(ascending=False)
```

Output

Severity 0.421728
RF-DP 0.326626
RA-HUMD 0.311420
OA-TEMP 0.303572
SA-HUMD 0.277498
SF-DP 0.214389
OAD-TEMP 0.189295
CHWC-DAT 0.171254
OA-CFM 0.158319
E_SF 0.156133
RA-CFM 0.152486

5.4 Decision tree classifiers

Decision tree classifiers have an inherent feature selection mechanism built into their algorithm. The splitting criteria of decision trees evaluate the importance or relevance of features when making decisions. Features that provide the most discriminatory power to distinguish different classes or improve the homogeneity of the resulting subsets are preferred for splitting. By examining the splitting decisions and feature importance, decision trees implicitly perform feature selection. Features that are not selected for splitting or have low importance are considered less relevant or informative for the classification task. Decision trees can also provide a measure of feature importance after training. This measure quantifies how much each feature contributes to the overall decision-making process of the tree. It considers the number of splits, the depth of the splits, and the impurity reduction achieved by each feature.

Input

```
from sklearn import tree
dt=tree.DecisionTreeClassifier()
dt.fit(X_train, Y_train)
```

```
dt_feat_importances=pd.DataFrame
({'Feature_names':X.columns ,'Importances':dt.feature_importances_})
dt_feat_importances.sort_values(by='Importances',ascending = False)
dt_features=dt_feat_importances.nlargest(8,['Importances'])
dt_1=dt_features['Feature_names']
retained_features_dt_v1=[]
for i in range (len(dt_1.index)):
retained_features_dt_v1.append(dt_1.values[i])
retained_features_dt_v1
```

Output

```
['Severity',
'HWC-VLV',
'CHWC-VLV',
'EA-DMPR',
'RA-DMPR',
'OA-DMPR',
'SA-CFM',
'RA-CFM']
```

5.5 Overall Results

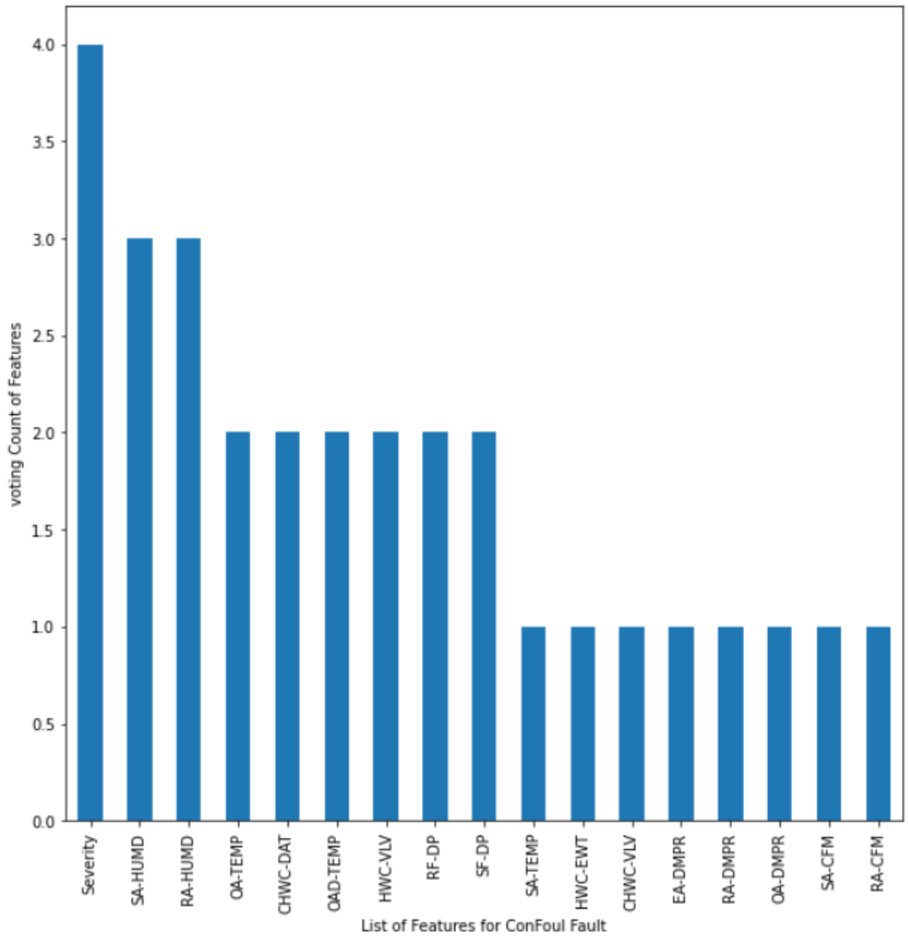

Figure 5.1: Vote-count for Feature Selection

The problem of fouling in heat exchangers can lead to decreased efficiency, increased energy consumption, and higher maintenance costs. By leveraging machine learning algorithms, we aimed to develop a predictive model that can accurately identify instances of fouling and provide timely alerts for maintenance and cleaning. To address this problem, we collected a comprehensive dataset containing various operational parameters and performance indicators of heat exchangers. Exploratory data analysis allowed us to gain insights into the data distribution, identify potential correlations, and understand the characteristics of fouling patterns (Refer Fig 5.1). Preprocessing techniques were employed to handle missing values, outliers, and feature engineering to extract relevant information. Several machine learning models, including KNN , decision trees, random forests, Lasso regression and support vector machines, were implemented . Feature selection methods were employed to identify the most influential features that contribute to fouling detection. we found that KNN achieved the highest performance in terms of accuracy and detection rates. The selected model demonstrated the ability to effectively classify instances of fouling, enabling timely detection and intervention to prevent further degradation of heat exchanger performance.

The developed machine learning model provide a valuable tool for monitoring heat exchangers in real-time and detecting fouling conditions. By integrating the model into the existing monitoring systems, maintenance personnel can be alerted to initiate cleaning procedures promptly, thus reducing energy waste, optimizing performance, and minimizing operational costs. It is important to note that further improvements and optimizations can be explored, such as incorporating additional data sources or exploring advanced machine learning algorithms like deep learning. Additionally, deploying the developed model in a real-world heat exchanger environment will require careful consideration of data collection, system integration, and model updates over time. Overall, this project contributes to the field of predictive maintenance and heat exchanger performance optimization by leveraging machine learning techniques to detect fouling. The outcomes of this research have the potential to enhance the efficiency and reliability of heat exchangers, benefiting industries that rely on these devices for their operations.

CHAPTER 6

TRAINING AND TESTING

The training dataset serves as the foundation for training the machine learning model. It contains labeled or known examples of input data along with their corresponding output or target values. During the training phase, the model learns from the patterns, relationships, and features present in the training data. The more diverse and representative the training dataset is, the better the model can capture the underlying patterns and generalize to unseen data. The testing dataset is used to evaluate the performance and generalization ability of the trained machine learning model. It consists of new, unseen data that the model has not been exposed to during the training phase. By measuring the model's performance on the testing data, how well it can predict or classify unseen instances accurately. This evaluation helps estimate the model's real-world performance and its ability to generalize to new data.

6.1 Machine Learning Algorithms used:

We trained multiple models with our dataset in order to experiment and find the model which gives the desired result and accuracy. The models used are listed below :-

6.1.1 K-Nearest Neighbour

KNN (k-nearest neighbors) is a simple and widely used machine learning algorithm that is used for both regression and classification problems. The algorithm works by finding the k-nearest neighbors of a given data point based on some distance metric and then making a prediction based on the class or value of those neighbors. KNN is a non-parametric algorithm, which means it does not make any assumptions about the distribution of the data. KNN is widely used in various domains such as image recognition, natural language processing, and recommendation systems. However, KNN can be computationally expensive and may not perform well with high-dimensional data or imbalanced datasets.

6.1.2 Decision Tree Classifier

A decision tree is a widely used machine learning algorithm for both classification and regression tasks. It is a hierarchical model that uses a tree-like structure to make decisions based on a sequence of rules or decisions that split the data into smaller and smaller subsets. At each node of the tree, a decision is made based on a specific feature or attribute of the data, and the data is split into two or more branches. The process continues recursively until the data is divided into subsets that are homogeneous in terms of the target variable. The decision tree algorithm builds the tree by selecting the best feature to split the data at each node based on some criterion such as information gain, gain ratio, or Gini index. The goal is to maximize the homogeneity or purity of the subsets and minimize the entropy or impurity of the data.

6.1.3 Support vector machine (SVM)

Support vector machine (SVM) is a widely used machine learning algorithm for classification and regression tasks. SVMs are based on the idea of finding a hyperplane that separates the data into two classes with the maximum margin. The hyperplane is defined as the line or plane that maximizes the distance between the closest data points of the two classes, called the support vectors. SVMs work by mapping the data to a high-dimensional feature space using a kernel function. The SVM algorithm then finds the hyperplane that best separates the data in the transformed space. SVMs can handle both linearly separable and non-linearly separable data by using different kernel functions.

6.1.4 Lasso regression

Lasso regression, also known as L1 regularization, is a popular method in machine learning used to prevent overfitting and select relevant features in a model. It is a linear regression technique that adds a penalty term to the objective function, which encourages the coefficients of the least important features to be shrunk to zero. The Lasso penalty term adds the absolute value of the coefficients multiplied by a tuning parameter lambda to the objective function, which results in a sparse solution where some of the coefficients are exactly zero. This allows the Lasso regression to perform feature selection and produce models that are easier to interpret. The lambda value determines the strength of the penalty term and controls the amount of regularization applied. The higher the lambda value, the more aggressive the regularization, and the more coefficients will be shrunk to zero. It has several advantages, including producing models that are more interpretable and performing feature selection. However, it can be sensitive to the choice of lambda value and may not perform well when the number of features is larger than the number of observations.

CHAPTER 7

SIMULATION

Simulation of the shell and tube heat exchanger in SolidWorks is a useful tool for designing and optimizing heat exchangers. It provides valuable insights into the performance of the heat exchanger and helps in making informed decisions about the design and operating parameters. The simulation results can be used to optimize the design of the heat exchanger, reduce energy consumption and improve its efficiency.

In order to generate the model, SOLIDWORKS software is used. ANSYS Fluent is used to analyse a model for a Shell and Tube heat exchanger. CFD analysis is performed in ANSYS by introducing boundary conditions. The boundary conditions such as temperature, pressure is used. Water is used as the cold fluid and ethylene was used as hot fluid. To enable the solution of equations, the fluid domain is continuously discretized into a discrete computational domain through the process of meshing. Mesh is helpful for breaking down the model geometry into several components that the solver may employ to create volume controls. The CFD model is designed to capture all physical events, including temperature, pressure, velocity, and heat transfer ratings, inside the computational domain.

An essential phase in a simulation study is simulation modelling. It focuses on building an effective simulation model that is as realistic as necessary to replicate important data for further analysis and to mimic the behaviour of the underlying system.

In this project, we will simulate the behaviour of a shell and tube heat exchanger using Ansys software. The objective of the simulation is to determine the heat transfer coefficient, pressure drop, and overall heat transfer rate of the heat exchanger.

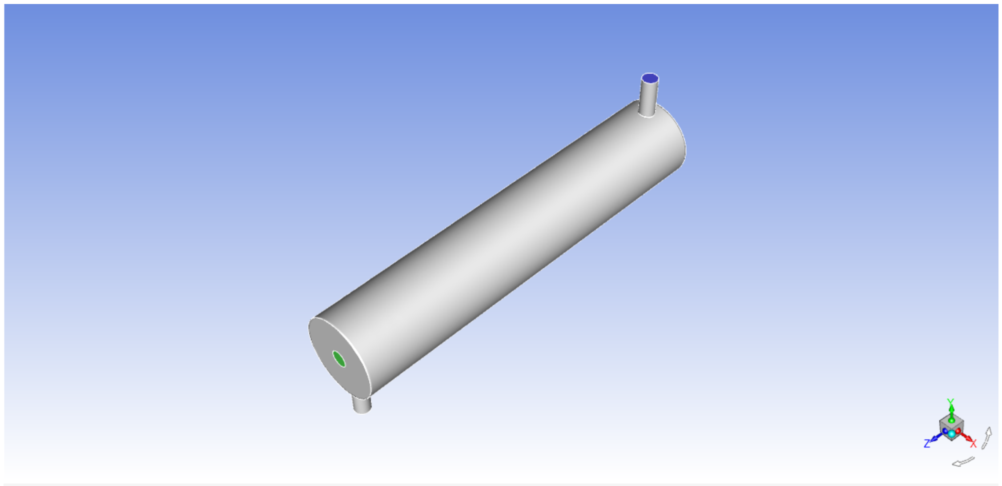

Figure 7.1: Heat exchanger model

7.1 Stepwise Procedure

- Define the properties of the fluids: The first step is to define the properties of the hot and cold fluids that will be used in the heat exchanger. The properties that need to be defined are density, viscosity, thermal conductivity, and specific heat.
- Design the heat exchanger: The next step is to design the shell and tube heat exchanger . The parameters that need to be defined are the diameter and length of the tube, the number of tubes, the diameter and length of the shell, the baffle spacing, and the number of baffles.
- Specify the operating conditions: The next step is to specify the operating conditions of the heat exchanger. The parameters that need to be specified are the inlet and outlet temperatures and flows of the hot and cold fluids.
- Simulate the heat exchanger: The final step is to simulate the behaviour of the heat exchanger using ANSYS software. The software calculates the heat transfer coefficient, pressure drop, and overall heat transfer rate of the heat exchanger.

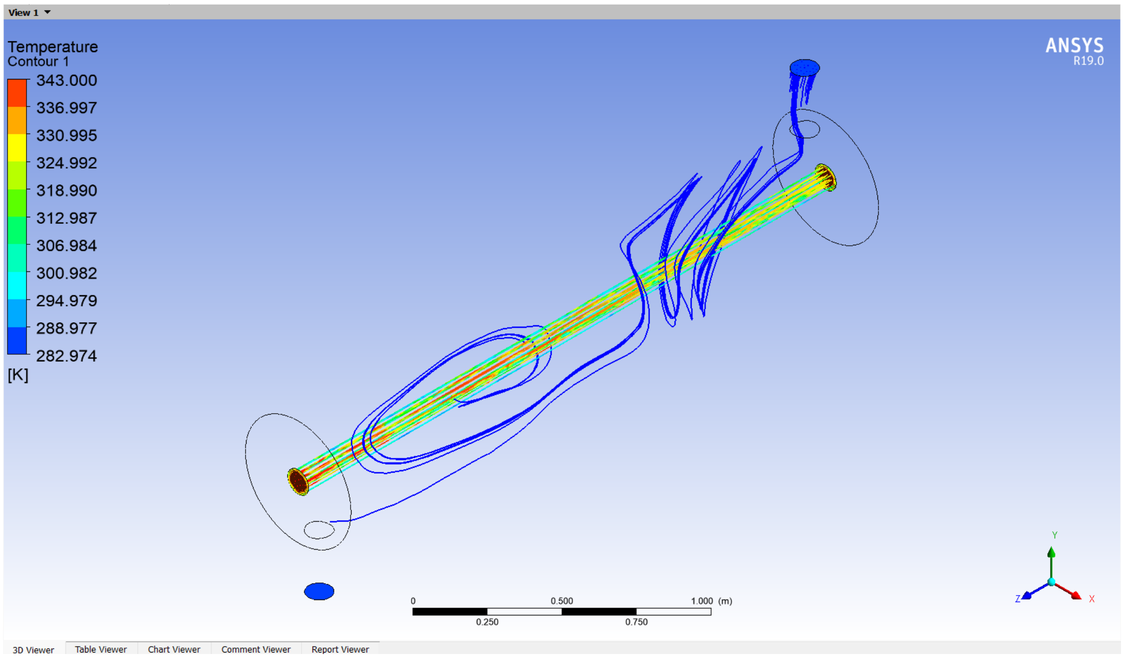

Figure 7.2: Temperature distribution in heat exchanger (ANSYS software)

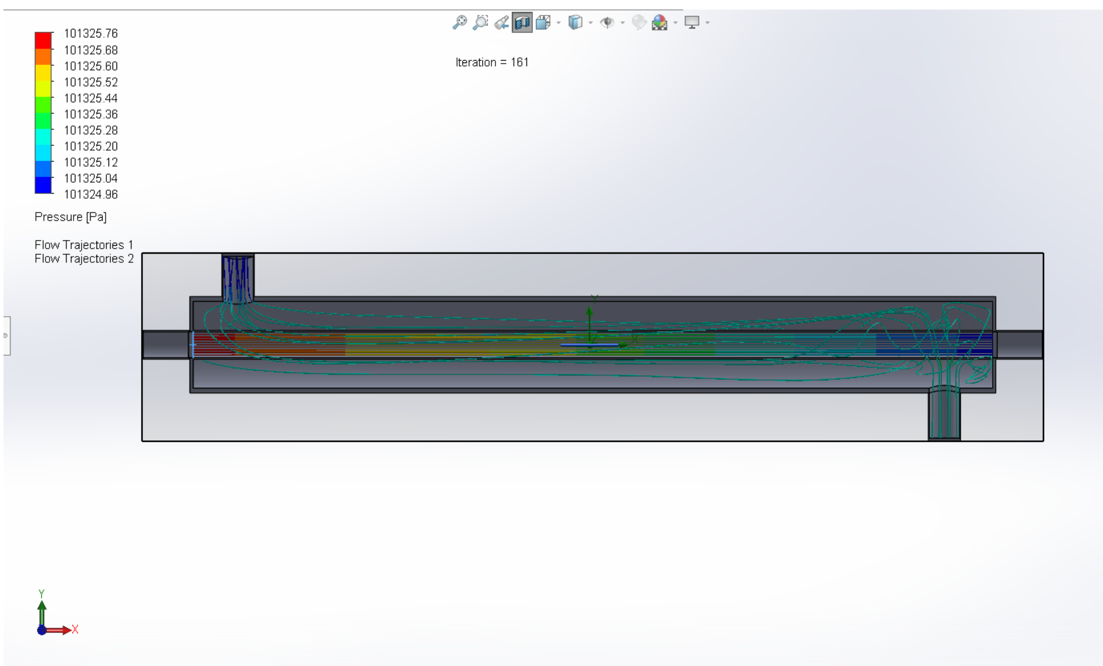

Figure 7.3: Temperature distribution in heat exchanger (SOLIDWORKS)

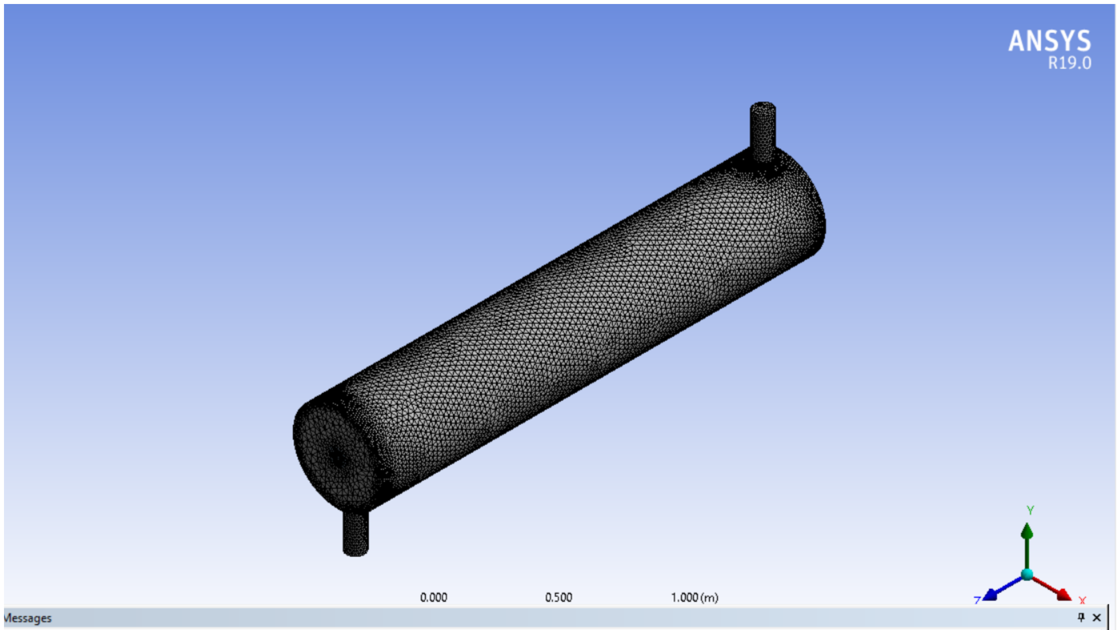

Figure 7.4: Meshing

In conclusion, the simulation of the shell and tube heat exchanger using ANSYS software has provided valuable information on the heat transfer performance of the heat exchanger. The simulation results provide information on the fluid flow patterns, heat transfer rates, and pressure drops in the heat exchanger.

7.2 List of software used

7.2.1 Anaconda Jupyter Notebook

1. Jupyter Notebook Overview: Jupyter Notebook is an open-source web application that allows users to create and share documents containing live code, equations, visualizations, and narrative text. It supports various programming languages, including Python, which made it an excellent tool for our project.

2. Setting up the Environment: To use the Jupyter Notebook, we first installed Python and the necessary libraries on our machine. We opted

for the Anaconda distribution, which includes Python and commonly used libraries such as NumPy, Pandas, and scikit-learn. These libraries provided us with the essential functionalities for data manipulation, preprocessing, and building our machine learning models.

3. Creating a Jupyter Notebook: Once the environment was set up, we created a new Jupyter Notebook by launching the Jupyter application. This opened a web-based interface where we could organize our project files and create new notebooks.

4. Writing Python Code: Inside the Jupyter Notebook, we used Python cells to write and execute our code. We could write individual code snippets, test them, and modify them as needed. We leveraged the rich ecosystem of Python libraries for various tasks, including data loading, feature engineering, model training, and evaluation.

5. Data Visualization: One of the significant advantages of Jupyter Notebook is its ability to display visualizations directly within the notebook interface. We utilized libraries such as Matplotlib and Seaborn to generate insightful plots and graphs, aiding in the exploration and analysis of the data. These visualizations allowed us to understand the patterns and characteristics of the heat exchanger data.

6. Building the Prediction Model: Using the data loaded in the notebook, we applied machine learning algorithms to develop a fault detection model. This involved preprocessing the data, splitting it into training and testing sets, training the model on the training set, and evaluating its performance on the testing set. We employed techniques like feature selection, hyperparameter tuning, and cross-validation to enhance the model's accuracy and robustness.

7. Iterative Development and Experimentation: Jupyter Notebook's interactive

nature facilitated an iterative development process. We could modify our code, re-run specific cells, and instantly observe the results. This flexibility allowed us to experiment with different algorithms, parameters, and preprocessing techniques, fine-tuning our model to achieve better performance.

7.2.2 ANSYS

1. Using ANSYS for Simulation: ANSYS is a widely used engineering simulation software that allows users to simulate and analyze complex physical phenomena. It offers a comprehensive suite of tools for structural, fluid, thermal, and electromagnetic simulations. In our project, we utilized ANSYS to model the behavior of a heat exchanger during a failure scenario.

2. Defining Failure Scenarios: To create realistic failure data, we first identified various failure scenarios that can occur in a heat exchanger. These could include tube leakage, fouling, corrosion, blockage, or other common issues. Each failure scenario was characterized by specific parameters such as the extent of leakage, location of blockage, or severity of corrosion.

3. Creating Simulation Models: Next, we created simulation models in ANSYS that accurately represented the geometry and properties of the heat exchanger under both normal and failure conditions. We used CAD software to develop the 3D geometry of the heat exchanger and imported it into ANSYS for further analysis.

4. Defining Material Properties: To simulate the behavior of the heat exchanger, we assigned appropriate material properties to the components within ANSYS. These properties included thermal conductivity, heat transfer coefficients, density, and other relevant parameters. We ensured

that the material properties aligned with the actual properties of the heat exchanger under normal and failed conditions.

5. Applying Boundary Conditions: To mimic real-world operating conditions, we applied realistic boundary conditions to the simulation models. This involved specifying the inlet and outlet temperatures, flow rates, and other relevant parameters. We considered both steady-state and transient conditions to capture the dynamics of the heat exchanger during failure scenarios.

6. Running Simulations: With the simulation models prepared and boundary conditions defined, we executed the simulations in ANSYS.

However, the software was unable to generate the desired results, for the following reasons: Unavailability of Higher Ansys Versions: The availability of the required Ansys version was a limiting factor. Ansys's capabilities and toolboxes continue to evolve with new releases, and the availability of specific features may depend on the version being used. If access to a higher version with necessary tools for heat exchanger simulation was not available, it restricted our ability to simulate failure scenarios accurately.

Computational Resource Limitations: Simulating complex heat exchanger behavior can be computationally intensive, requiring significant computational resources such as processing power and memory. In cases where the available computer hardware or software licenses were limited, we faced challenges in running computationally demanding simulations within reasonable timeframes.omputational Resource Limitations: Simulating complex heat exchanger behavior can be computationally intensive, requiring significant computational resources such as processing power and memory. In cases where the available computer hardware or software licenses were limited, we faced challenges in running computationally demanding simulations within reasonable timeframes.

7.2.3 MATLAB

- Simulating Failure Data with MATLAB: MATLAB provides powerful capabilities for mathematical modeling, simulation, and data analysis. Leveraging its functionalities, we intended to create synthetic failure datasets by simulating the behavior of faulty heat exchangers. The simulation process involved defining failure scenarios, implementing mathematical models, and generating simulated data.
- Challenges and Limitations: Availability of Higher MATLAB Versions: The availability of the required MATLAB version was a limiting factor. MATLAB's capabilities and toolboxes continue to evolve with new releases, and the availability of specific features may depend on the version being used. If access to a higher version with necessary tools for heat exchanger simulation was not available, it restricted our ability to simulate failure scenarios accurately.
- Computational Resource Limitations: Simulating complex heat exchanger behavior can be computationally intensive, requiring significant computational resources such as processing power and memory. In cases where the available computer hardware or software licenses were limited, we faced challenges in running computationally demanding simulations within reasonable timeframes.
- Alternative Approaches: Despite the limitations, we explored alternative approaches within the constraints imposed by the software and computational resources
- Simplified Models: We attempted to develop simplified mathematical models in MATLAB that could capture certain failure scenarios. These models aimed to replicate specific failure behaviors, considering relevant parameters and their impact on heat exchanger performance. Simplified

models allowed us to overcome some limitations by approximating the behavior of real failures.

CHAPTER 8

CONCLUSION

In this project, our objective was to develop a machine learning model for the detection of fouling in heat exchangers. The detection of fouling is crucial in maintaining the efficiency and performance of heat exchangers, as fouling can lead to reduced heat transfer rates and increased energy consumption. By leveraging machine learning techniques, we aimed to provide an automated and accurate method for identifying fouling in heat exchangers.

To achieve our objective, we followed a systematic approach. We collected a comprehensive dataset containing various operational parameters and historical fouling data. After pre-processing the data by handling missing values and normalizing numerical features, we conducted feature selection and engineering to identify the most relevant variables .With the prepared dataset, we developed and trained multiple machine learning models, including logistic regression, decision trees, random forests, and neural networks. Through careful evaluation and comparison, we identified the best-performing model, which exhibited high accuracy, precision in detecting fouling events.

The trained model demonstrated a significant improvement in identifying fouling instances compared to traditional manual inspection methods. By analysing the model's predictions, we observed its effectiveness in accurately detecting fouling events, thus enabling timely maintenance interventions. This automated approach can lead to enhanced heat exchanger performance, reduced operational costs, and minimized downtime. The practical applications and benefits of our fouling detection model are substantial. It provides an automated system that can detect fouling early, facilitating proactive maintenance and cleaning. By addressing fouling issues promptly, energy efficiency is optimized, and the risk of costly repairs caused by severe fouling is reduced. Furthermore, the model can aid in predictive maintenance strategies, allowing for proactive measures to prevent fouling-related problems.

CHAPTER 9

FUTURE SCOPE

While our model has shown promising results, there is room for future improvement. Collecting additional data from diverse heat exchanger systems and operational conditions can enhance the model's robustness and generalization. Exploring advanced machine learning techniques, such as ensemble methods or deep learning architectures, may further enhance the accuracy and performance of the model. Continuous model monitoring and retraining based on real-time data will ensure its effectiveness in dynamic operational scenarios. Software's such as Ansys or MATLAB can be used to generate dataset when fouling failure occurs .

In conclusion, our project demonstrates the effectiveness of machine learning in detecting fouling in heat exchangers. The developed model provides an automated, accurate, and efficient solution for identifying fouling events promptly, enabling proactive maintenance and optimizing heat exchanger performance. By implementing this solution, industries can mitigate fouling-related challenges, improve energy efficiency, and reduce operational costs.

9.1 Difficulties Faced

- To initiate the simulation of the heat exchanger, we embarked on utilizing MATLAB to explore its features and capabilities in developing a comprehensive simulation model. However, our progress in MATLAB was hindered when we encountered a hurdle in acquiring a crucial library called Reds Library. Unfortunately, due to its high cost, we were unable to proceed with our task on MATLAB.

- During the transition from MATLAB to ANSYS software, we successfully designed a simple shell and tube heat exchanger model. Constant values for parameters such as temperature, pressure, and velocity were assigned to facilitate the initial simulation. Our subsequent objective was to generate a dataset comprising various values within ANSYS.
- In ANSYS, specifically using ANSYS Workbench, we familiarized ourselves with the software's functionalities. Consequently, we constructed a comprehensive heat exchanger model within ANSYS Fluent, employing a similar procedure as in SolidWorks for simulation creation.
- However, as we progressed, we encountered a limitation whereby the creation of a dataset model became unfeasible. It became apparent that our approach of obtaining a dataset for different combinations of temperature, pressure, and other parameters would require alternative methods or adjustments in our workflow.

BIBLIOGRAPHY

[1] Olga Arsenyeva, Olexander Matsegora, Petro Kapustenko, Anna Yuzbashyan, Jiri Jaromir klemes. “The water fouling development in plate heat exchangers with plates of different corrugations geometry”

[2] M. Trafczynski, M. Markowski, K. Urbaniec, P. Trzcinski, S. Alabrudzinski, W. Suchecki. “Estimation of thermal effects of fouling growth for application in the scheduling of heat exchangers cleaning”

[3] Chao Shen, Chris Cirone, Liangcheng Yang, Yiqiang Jiang, Xinlei Wang. “Characteristics of fouling development in shell-and-tube heat exchanger: Effects of velocity and installation location”

[4] Mehdi Mehrabi and David Yuill. “ Fouling and its effects on air-cooled condensers in split system air conditioners(RP-1705)

[5] Parag Patil, Babji Srinivasan, Rajagopalan Srinivasan. “Monitoring fouling in heat exchangers under temperature control based on excess thermal and hydraulic loads”

[6] M. Indumathy, S.Sobana, Rames C. Panda. “Modelling of fouling in a plate heat exchanger with high temperature pasteurization process”

[7] Jialin Song, Zhibin Liu, Zhongjiao Ma, Jili Zhang. “Experimental investigation of convective heat transfer from sewage in heat exchange pipes and the construction of a fouling resistance-based mathematical model”

[8] Fakhrony Sholahudin Rohman , Dinie Muhammad, Sudibyo, Muhammad Nazri Murat, Ashraf Azmi. “Application of feed forward neural network for fouling thickness estimation in low density polyethylene tubular reactor”

[9] Saleh Hosseini, Amith Khandakar, Muhammad E.H. Chowdhury , Mohamed Arselene Ayari, Tawsifur Rahman, Moajjem Hossain Chowdhury, Behzad Vaferi. “ Novel and robust machine learning approach for estimating the fouling factor in heat exchangers”