PREDICTION OF NUCLEATE AND FILM BOILING HEAT TRANSFER USING ARTIFICIAL NEURAL NETWORK

THESIS SUBMITTED IN PARTIAL FULFILMENTS OF THE REQUIREMENT FOR THE DEGREE OF MASTER OF ENGINEERING IN MECHANICAL ENGINEERING UNDER FACULTY OF ENGINEERING AND TECHNOLOGY

Submitted by

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Academic Session: 2022-2024

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DECLARATION OF ORIGINALITY AND COMPLIANCE OF ACADEMIC ETHICS

I hereby declare that the thesis entitled "**PREDICTION OF NUCLEATE AND FILM BOILING HEAT TRANSFER USING ARTIFICIAL NEURAL NETWORK**" contains literature survey and original research work by the undersigned candidate, as a part of his *MASTER OF ENGINEERING IN MECHANICAL ENGINEERING under the DEPARTMENT OF MECHANICAL ENGINNERING*, studies during academic session 2022-2024.

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This is to certify that the thesis entitled "**PREDICTION OF NUCLEATE AND FILM BOILING HEAT TRANSFER USING ARTIFICIAL NEURAL NETWORK**" is a bonafide work carried out by SAPTARSHI DAS under our supervision and guidance in partial fulfilment of the requirements for awarding the degree of Master of Engineering in Mechanical Engineering under Department of Mechanical Engineering, Jadavpur University during the academic session 2022-2024.

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CERTIFICATE OF APPROVAL

The foregoing thesis, entitled "**PREDICTION OF NUCLEATE AND FILM BOILING HEAT TRANSFER USING ARTIFICIAL NEURAL NETWORK**" is hereby approved as a creditable study in the area of Mechanical Engineering carried out and presented by SAPTARSHI DAS in a satisfactory manner to warrant its acceptance as a prerequisite to the degree for which it has been submitted. It is notified to be understood that by this approval, the undersigned do not necessarily endorse or approve any statement made, opinion expressed and conclusion drawn therein but approve the thesis only for the purpose for which it has been submitted.

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ACKNOWLEDGEMENT

I would like to record here my gratitude to all who supported me and gave constructive suggestions during the completion of this paper.

Separately, I express my deepest gratitude to **Prof. Koushik Ghosh**, Department of Mechanical Engineering and **Prof. Saikat Mookherjee**, Department of Mechanical Engineering, for their invaluable guidance. The regular discussions and idea-sharing with my thesis supervisors really helped me to improve my knowledge day by day my research related problems. At the beginning of this work, they gave me the valuable instruction that properly guided me in right path to accomplish this paper. It was really a pleasure work under their supervision.

I sincerely believe that I was fortunate enough to have come across **Prof. Koushik Ghsoh**, who can inspire someone to work wonders. It would really have been not possible for me to complete this thesis without his assistance, proper guidance and motivation. He always helped me during the critical phase of this thesis and was always available for me for any query, whether it's a telephonic or a face to face discussion. Above all he enhanced my confidence and guided me throughout my work.

I firmly believe that I was fortunate to have met **Prof. Saikat Mookherjee,** who has the ability to motivate people to do great things. Without his aid, the right direction, and the determination to finish this thesis, it would not have been feasible for me to do so. He always supported me as I worked through the revision process for this thesis and was always there to answer any questions I had, whether they were best answered over the phone or in person. Above all, he boosted my confidence and helped me get the job done.

I truly think it was a stroke of luck that I met **Prof. Dipankar Sanyal** and **Dr. Sourav Sarkar**, Department of Mechanical Engineering, who have the ability to motivate others to achieve great things. Without their help, the right direction, and the inspiration they provided, I definitely would not have been able to finish this thesis. They consistently supported and assisted me during my thesis key stage, always available for questions via phone or in-person meetings, boosting my confidence along the way.

I also tender my sincere gratitude to **Mr. Saumendra Nath Mishra**, PhD scholar, Department of Mechanical Engineering, whose continuous guidance helped me a lot in carrying out a major portion of my work. Without his wise and valuable advices, it would not be possible to prepare such a thesis.

I would like to thank **Mr. Manish Kumar Manna** and **Mr. SK. Hasan Raja**, PhD scholars, Department of Mechanical Engineering, for giving me valuable suggestions and the instant ideas which played an important part to process the thesis.

I also like to thank **Mr. Koushik Samnata**, Department of Mechanical Engineering, for implying his knowledge in the thesis work and his assistance in all over the work.

I would like to thank **Mr. Sudipta Saha,** PhD scholar, School of Nuclear Studies and Application, for his instant help and providing ideas.

I am highly indebted to all my professors of **NEPTUNE** lab, their guidance and supervision as well as for providing necessary information regarding thesis and also for their support in completing my master's thesis.

I would like to express my gratitude towards my parents and my younger brother for their kind cooperation and encouragement which helped me in the completion of my master's thesis.

Finally, my thanks and appreciations also go to my dear friends in developing my master's project and people who have willingly helped me out with their abilities.

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Nomenclature		Subscripts		Greek Symbols	
$q"$	Heat flux	*sat*	Saturation	δ	Vapor film thickness
$q"_{boiling}$	Boiling heat flux	*w*	Wall	β	Coefficient of volumetric thermal expansion
ΔT, ΔT_{sat}	Degree of superheat	*max*	Maximum value	ν	Kinematic viscosity
T_{wall}	Temperate at wall	*min*	Minimum value	α	Thermal diffusivity
T	Temperature	*CHF*	Critical heat flux	μ	Dynamic viscosity
u, v	Velocity components	*i*	Interface	ρ	Density
x, y	Coordinates	∞	Free stream	σ	Stefan–Boltzmann constant
Nu	Nusselt number	*l*	Liquid-phase	ε	emissivity
Ra	Rayleigh number	*v*	Vapour-phase	σ_t	Surface tension
k	Thermal conductivity	*nc*	Natural convection		
g	Acceleration due to gravity	nb	Nucleate boiling		
D	Diameter	*hs*	High superheat		
L	Characteristic length	*ls*	Low superheat		
Pr	Prandlt number	*lsnc*	Low superheat natural convection		
h_{fg}	Enthalpy of vaporization	*lsfc*	low superheat forced convection		
c_p	Specific heat at constant pressure	*sup*	Superheated condition		
h	Heat transfer coefficient	*sub*	Subcooling condition		
p	Pressure	*conv*	Convective		

P_c	Critical pressure				
ΔP	Pressure difference				
M	Molar mass				
R_p	Particle size (nm)				
Ja	Jakob number				
Gr	Grashof number				
Re	Reynolds number				
h_0	Reference heat transfer coefficient				
D_b	Bubble departure diameter				
l^*	Modified characteristic length				
$Nu_{expt,total}$, $Nu_{expt,tot}$	Total experimental Nusselt number				
$Nu_{expt,conv}$	Convective Nusselt number from the experiment				
Nu_{rad}	Nusselt number due to radiation				
$Nu_{scale,tot}$	Total Nusselt number by scale analysis				
$Nu_{ann,tot}$	Total Nusselt number from ANN prediction				
L_c	Instability length scale $= \left[\frac{\sigma_t}{g(\rho_l-\rho_v)}\right]^{1/2}$				

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Chapter 1

Introduction

1.1. Background

Boiling heat transfer, especially Pool boiling is one of the most crucial mechanisms in heat transfer. Pool boiling is the boiling process that takes place on a solid surface immersed in a liquid, typically water, due to a temperature difference between the surface and the liquid. Pool boiling occurs when there is no bulk motion of the fluid. In pool boiling, the fluid remains stationary and any movement within the fluid is caused by the natural convection flow. The reason it is referred to as "pool" boiling is because vapour bubbles develop and accumulate on the heated surface before separating and moving upwards through the liquid. Pool boiling is a crucial occurrence in a variety of industrial applications, such as power production, refrigeration, cooling for electronics, nuclear reactions and some other engineering applications [1]. Comprehending and managing pool boiling can enhance the effectiveness and functionality of the above systems. Nucleate pool boiling is the most important stage of pool boiling. The involvement of forced convection, phase change, presence of two phases and high rate of heat flux are present here. The significance of nucleate boiling comes from its capacity to eliminate large amounts of heat in a short amount of time and space from a heated surface, achieving this heat transfer with minimal thermal force. The process is used in a range of energy conversion and heat exchange systems due to its effectiveness.

Another important regime, which is in a highlight, is the film boiling regime. In this region, the involvement of high temperature, conduction-convection through vapour film and thermal radiation across the vapour film is present. Film boiling is not widely used commercially due to the undesirability of high temperatures. However, film boiling is an inevitable mode of boiling heat transfer for severe accident of nuclear plants, quenching of components from high temperature etc.

In order to understand the pool boiling mechanism, it is necessary to know about the pool boiling curve, pool boiling regimes and the stages of the bubble formation.

1.1.1. Pool Boiling Curve

During the initial stages of investigating heat transfer, scientists witnessed how liquids reacted to being heated. It was observed that when a liquid is heated above a specific temperature, it begins to boil and bubbles form on the surface being heated. The temperature difference between the heated surface or wall and the liquid is referred as wall superheat or excess temperature. As the wall superheat increases, there is a continuous variation in the heat flux from the heating surface. The nature of variation can be shown by a curve, called "Pool boiling curve" [2], which was proposed by Nukiyama [3]. The boiling curve in the figure shows the different regimes based on heat flux and excess temperature. It was noticed that the bubble formation increased with increasing the degree of superheat. Although the pool boiling curve, which is shown in the Fig. 1.1, represents water at 1 atm pressure, the overall shape of the boiling curve is consistent across various other liquids or coolants. The curve shows different stages (natural convection, nucleate boiling, transition boiling, film boiling), with each stage having unique heat transfer mechanisms and surface temperature variations.

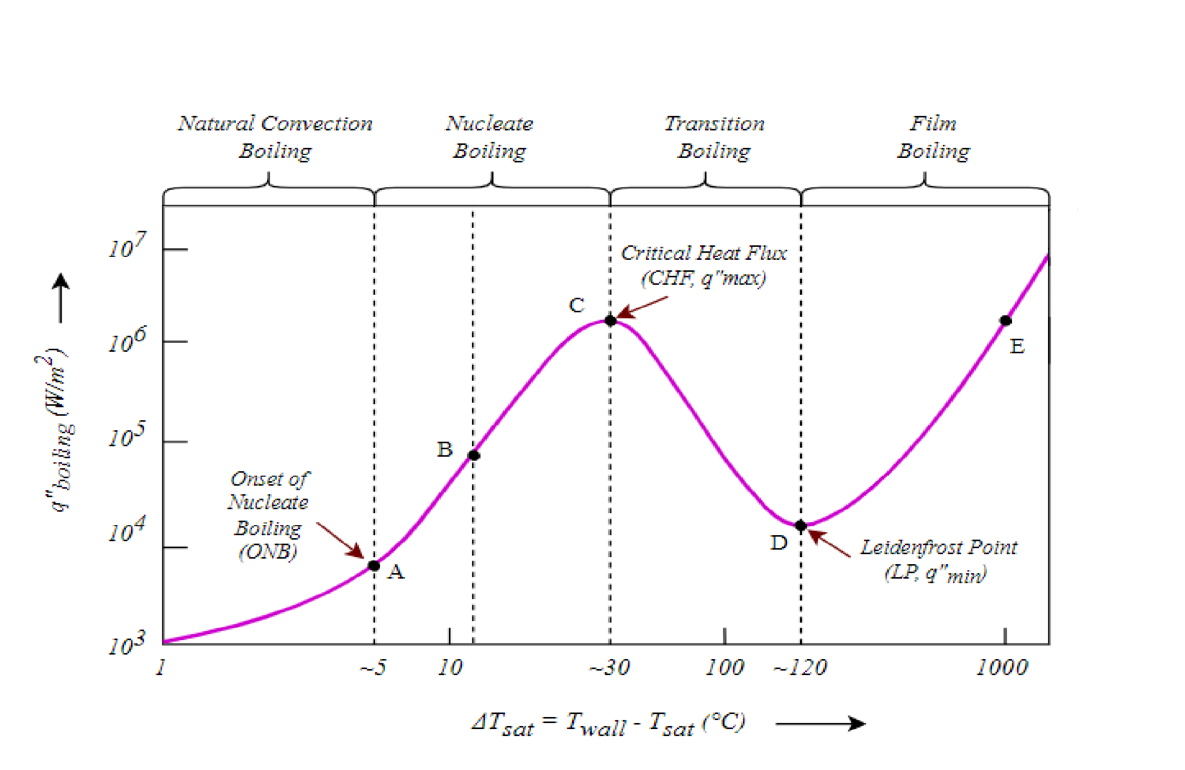


Fig. 1.1: Pool Boiling Curve at 1atm Pressure

From the above figure, those stages, nature of heat flux with the wall superheat can be observed easily. Factors such as liquid properties, surface roughness, pressure, and initial temperature determine the shape and position of the pool boiling curve. Measuring heat flux and surface temperature under controlled conditions is necessary for the experimental determination of the curve.

1.1.2. Pool Boiling Regimes

The pool boiling curve is separated into four distinct regions based on the excess temperature and there is a continuous change in heat flux throughout all the four regimes [4]. Variations in pool boiling regimes, such as nucleate boiling and film boiling, occur as heat transfer mechanisms and fluid dynamics shift with increasing heat flux on a heated surface. Different types of boiling regimes in a pool are necessary for maximizing heat transfer, creating heat exchangers, and ensuring the safe functioning of systems that involve boiling liquids. The regimes are as follows:

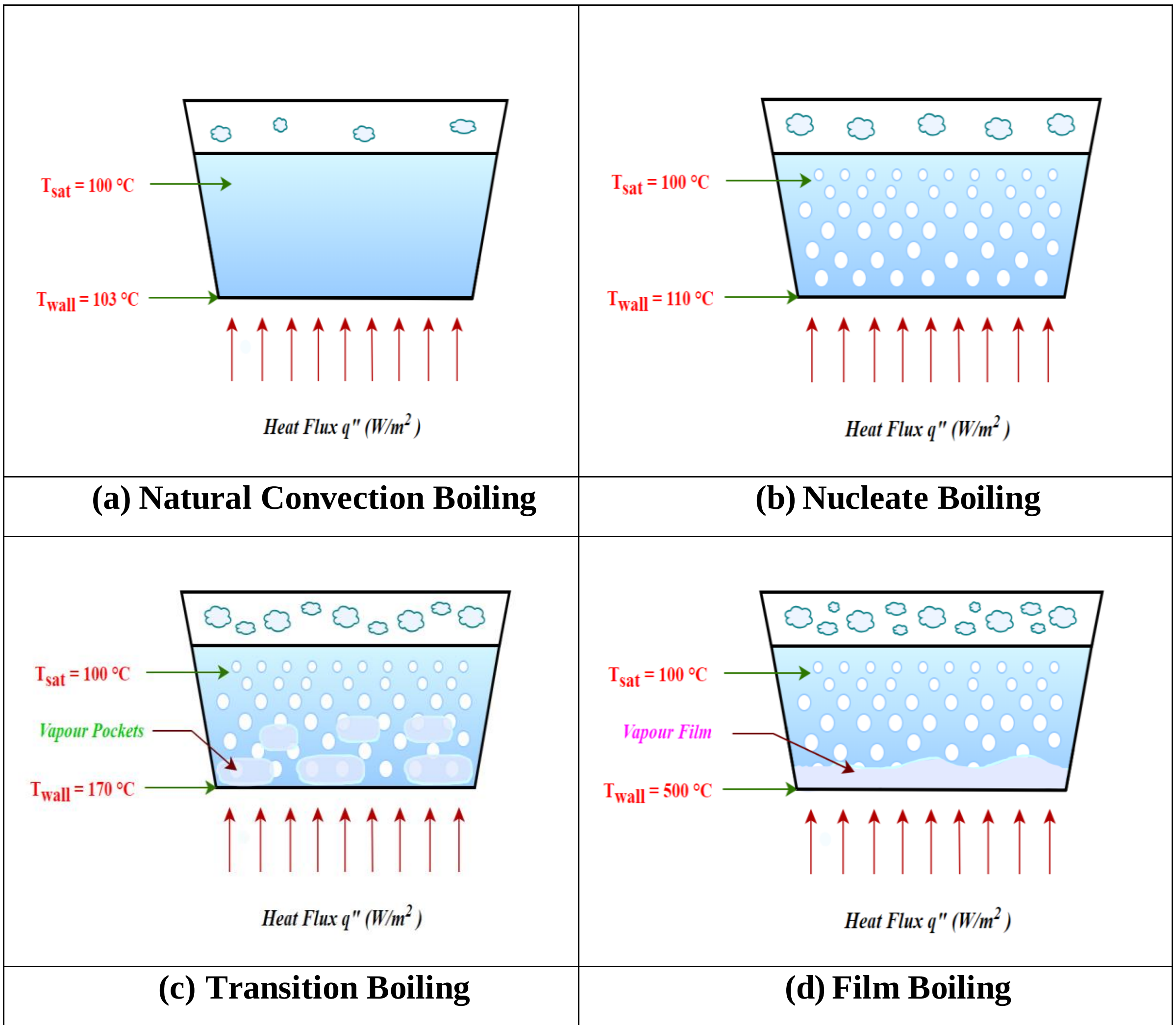
i. Natural Convection Boiling- $\Delta T_{sat} < 5°C$

ii. Nucleate Boiling- $5°C < \Delta T_{sat} < 30°C$

iii. Transition Boiling- $30°C < \Delta T_{sat} < 200°C$

iv. Film Boiling- $200°C < \Delta T_{sat}$

These four regimes can be obtained by increasing the wall superheat gradually. Due to the wall superheat, heat flux changes continuously. The highest amount of heat flux is achieved in the nucleate boiling stage. Thus, it is more efficient to run the boiler in this mode to maximize heat transfer and heat flow. The Fig. 1.2 describes the nature of water pool for boiling.



(a) Natural Convection Boiling **(b) Nucleate Boiling**

(c) Transition Boiling **(d) Film Boiling**

Fig. 1.2: Different Pool Boiling Regimes

The above figures show the nature of bubble formation with increasing the wall temperature for the different regimes of pool boiling. The physical significance of each regimes of pool boiling are mentioned below in details:

A. **Natural Convection Boiling:** For pure substances to boil in heat transfer, a specific condition must be met, i.e., wall temperature equals the saturation temperature. However, boiling typically doesn't happen until the liquid is heated slightly above its saturation temperature in actual experiments. In order to maintain the creation of vapour, the temperature of the surface needs to be slightly higher than the saturation temperature. When the liquid is heated above its boiling point (for water its 100°C), the heat is exchanged between the wall and the liquid with no bubbles forming. The liquid near the surface wall heats up slightly above its boiling point and turns into vapour at the boundary between liquid and gas. Initially, there is a small temperature difference (< 5°C) resulting in a small heat flux. Bubble formation will happen once the superheat temperature rises, but before point A in Fig. 1.1, the movement of fluid is mainly influenced by single phase natural convection currents. Thus, this region is known as the Natural Convection Boiling region of boiling curve [5], which is characterized by a small temperature difference and the heat is transferred through convective flowing movements in the liquid.

B. **Nucleate Boiling:** Point A in Fig. 1.1 is the beginning of nucleate boiling, when bubbles start to develop and separate from a heated surface in a liquid. It is an important step during boiling when the temperature at the interface between solid and liquid exceeds the saturation temperature of the liquid. In simple words, when the liquid is heated, the temperature increases until small bubbles begin to form at specific points on the heated surface. These bubbles subsequently disconnect and float upwards in the liquid, taking heat with them. This is the process of nucleate boiling [6]. Prior to this moment, the liquid could be warmed up, however, it stays quite tranquil with no visible signs of bubbling. It is commonly known as the Onset of Nucleate Boiling (ONB) [7].

Nucleate boiling involves the creation of steam bubbles on a surface to transfer heat into a fluid flow, enhancing heat transfer. The process begins when bubbles form at specific locations referred to as Nuclei [8]. These bubbles implode upon contact with the liquid, creating turbulence that further increases heat transfer. The increase in heat flux with wall superheat leads to the rapid rise of bubbles towards the surface until reaching the Critical heat flux (CHF) [9] point, where the heat flux reaches its maximum. For nucleation to occur, the liquid must be superheated, with two types of nuclei possible: high-energy molecule clusters or voids caused by pressure changes within the liquid, or voids on external surfaces created by foreign materials. Nucleate boiling is an important area for technical applications due to its ability to transfer thermal energy efficiently, but the heat flux cannot be continuously increased beyond the CHF point.

In the Nucleate boiling zone, critical heat flux is the maximum heat flux and a threshold phenomenon. To increase heat transfer, liquid must be continuously heated, but vapor blocking prevents absorption of heat, leading the heater surface to absorb heat instead. The surface absorbs excess energy from temperature rise, releasing it with further temperature increase. The surface can't handle more heat and may not reach the point to turn off before turning to liquid, known as Burnout [10]. CHF is burnout heat flux, and most heaters operate below this level to avoid catastrophic results. Metals with high melting points can help prevent burnout, but it's not a concern for cryogenic applications.

Further increasing the temperature after CHF may result in burnout, which can impede the surface's ability to effectively release heat and potentially lead to equipment breakdown. In order to prevent this, the majority of boiling processes work at levels lower than CHF to ensure consistent heat transfer and avoid the risk of burnout.

C. **Transition Boiling:** After passing point C, there is a noticeable shift in heat transfer with a steep drop in heat flow as the surface temperature increases from 30°C to 200°C. The reduction is caused by the creation of a vapour layer between the hot surface and the liquid. After surpassing the Critical Heat Flux (CHF), there is a quick shift from efficient nucleate boiling to ineffective film boiling. Point D, named the Leidenfrost point [11], signifies the point at which liquid droplets float above the surface without touching it directly. This vapour film that is not steady can cause fluctuations in heat transfer and interrupt the boiling process, known as Transition boiling or Unstable film boiling [12]. When the heat flux decreases below the Leidenfrost point, the film will break, resulting in the reappearance of nucleate boiling, also referred to as Return to Nucleate Boiling (RNB) [13]. The transition from nucleate to film boiling is known as Boiling crisis or Departure from Nucleate Boiling (DNB) [14], occurring when heat flux exceeds a critical limit. Film boiling leads to a significant decrease in heat transfer effectiveness, resulting in a quick rise in surface temperature, potentially causing surface burnout or equipment malfunction.

D. **Film Boiling:** After the Leidenfrost point, heat flux results in a complete surface coverage with a film of vapour. This greatly decreases the rate of heat transfer through convection [15]. In this case, the heat transfer occurs through both radiation and conduction to the vapour. This region in the pool boiling is known as Film Boiling [16]. Film boiling occurs when the system pressure decreases or the flow rate is reduced. In this situation, the bubbles are unable to escape the heat transfer surface rapidly [17]. Similarly, raising the temperature of the heat transfer surface results in the formation of additional bubbles. When the excess temperature rises (more than 200°C), a greater number of bubbles are produced that cannot be effectively removed. The bubbles increase in size and cluster, coating small sections of the heat transfer surface with a layer of steam [18]. Film boiling serves as a barrier between heat surfaces and liquids, crucial for precise thermal control and efficient heat transfer in technical applications. Its essential role in industrial and scientific fields lies in managing high thermal loads and regulating heat effectively.

1.1.3. Film boiling in vertical flat plate

Film boiling on a vertical flat plate can be observed fwith the presence of stable vapour film. By applying heat on a vertical flat plate, the motion of the vapour goes upwards, while the bulk liquid stays stationary. The film boiling can be accommodated as subcooled, saturated and superheated conditions. The qualitative velocity and the temperature profile under film boiling in vapour and liquid phases are shown Fig. 1.3a). The vapour film goes upwards with a wavy form which is shown in Fig. 1.3 (b). A schematic diagram is shown in the below figure to organize the flow nature which is taken from Das et al. [19].

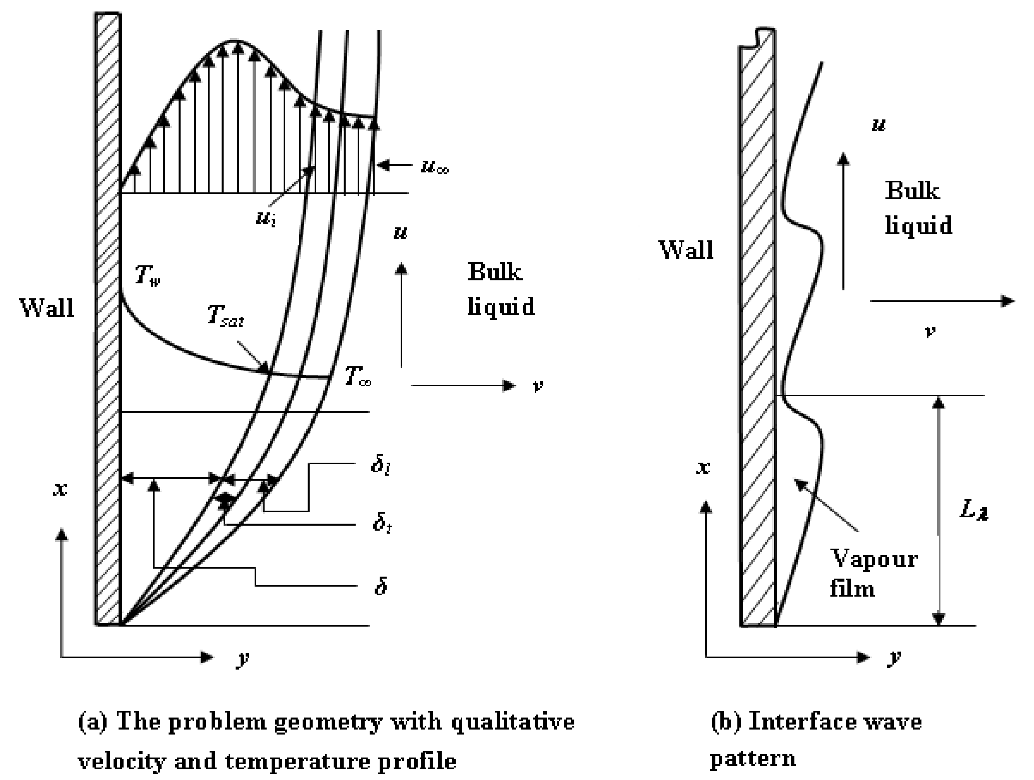


Fig. 1.3: Film boiling in Vertical Flat Plate

1.2. Objective and Motivation

Pool boiling is a highly effective technique for heat dissipation in industrial environments because the boiling liquid can reach high heat fluxes while keeping wall superheat temperatures low (i.e. the temperature difference between the surface being heated and the fluid). The different stages of pool boiling can be observed by the physical changes of the liquid pool with changing the temperature. Natural convection boiling, Nucleate boiling and Film boiling can be analysed by several experimental results and multiple empirical correlations as well. But, sometimes there are few difficulties appear in order to analyse the pool boiling heat transfer experimentally, such as some external and environmental influences and high set-up cost for experiments. Some of the major difficulties come while solving the heat transfer problem in pool boiling are mentioned below:

A. **Multi-Physics Nature:** Pool boiling includes various physical processes like fluid dynamics, heat transfer, phase change (boiling and condensation), and occasionally radiation. Combining these various elements into a cohesive mathematical framework can be complicated and necessitates thorough examination of the role of each phenomenon.

B. **Phase Change Dynamics:** Boiling is a process in which liquid turns into vapour on a heated surface. Accurately representing this phase transition requires a thorough comprehension of factors like bubble formation, expansion, detachment, and their interaction with the surrounding liquid. It can be difficult to capture these dynamics in simulations or analytical models, especially when dealing with varying heat fluxes and surface conditions.

C. **Variation of Heat Transfer Coefficient:** The rate at which heat is transferred while boiling can change greatly based on factors like temperature, pressure, surface roughness, and liquid characteristics. Accurately forecasting these changes in various situations (such as nucleate boiling, transition boiling, and film boiling) is crucial but difficult because they rely on local parameters.

D. **Flow Regimes and Instabilities:** Boiling processes can shift between nucleate boiling, transition boiling, and film boiling, each characterized by different heat transfer methods. Anticipating these changes with precision and comprehending the circumstances in which they happen (such as critical heat flux) is crucial but can be difficult because of the intricate connection between physical factors and fluid dynamics.

E. **Experimental Challenges:** Performing experiments to confirm models and theories of pool boiling can be complex and require a lot of resources. Precisely managing experimental conditions such as pressure, heat flux, and surface conditions is necessary to isolate specific phenomena or regimes, which demands advanced experimental setups and meticulous data analysis.

Surface effects, scale effects, and numerical simulation through CFD contribute to the complexity of solving heat transfer problems. Empirical correlations, such as heat flux, Heat Transfer Coefficient (HTC), and Nusselt number (Nu), also involve uncertainty when predicting heat transfer nature and amount. These correlations vary in accuracy based on the liquid analysed, geometry, physical properties, and other conditions, leading to an inherent uncertainty in determining heat transfer rate and efficiency. Extensive research and practical experience over a century have not fully explained the complexities of pool boiling heat transfer. Theories on boiling phenomena have not been very useful, so practical calculations heavily rely on empirical correlations from experiments. Global research on boiling phenomena is ongoing to further understand this area.

Further analysis is needed to predict pool boiling efficiency with liquids and coatings, and the correlation between heat flux and superheat. Experimental difficulties and uncertain correlations complicate analysis. Overcoming challenges in pool boiling heat transfer analysis is crucial. Solving numerically can help find solutions for heat transfer in pool boiling.

This thesis work is taken up to overcome the above obstacles for analysing the heat transfer for pool boiling. The objective of the thesis is to predict the Nusselt number with better accuracy for different pool boiling regimes for different conditions than the standard empirical correlations through non-dimensional analysis and to compare those results with the experimental results. The aim of the thesis is to fulfil the research gap found in order to solve the problems on pool boiling heat transfer, especially the nucleate pool boiling and film boiling (both pool boiling and flow film boiling). The whole thesis work is based on the prediction of heat transfer using artificial neural network (ANN).

1.3. Literature Review

Numerous scientists and researchers have conducted experiments to study pool boiling behaviour and performance, leading to the development of experimental methods and theoretical models. Trials were done to analyse heat transfer, temperature differences, bubble movements, and surface properties under various conditions. Mathematical models were created to explain heat transfer processes, taking into account factors like surface roughness, fluid characteristics, and thermodynamic states. A wide range of literature exists that provides analytical or numerical analysis for comparison and further research on enhancing boiling heat transfer.

McAdams [20] developed a natural convective heat transfer relationship using experimental data from vertical plates and large diameter tubes. The model is based on scale analysis of boundary equations, Boussinesq approximation, and boundary layer approximation. The equations that are commonly utilized are as follows:

$$Nu = 0.148\, Ra^{1/3} \qquad 10^{10} < Ra < 10^{11} \tag{1.1}$$

$$Nu = 0.48\, Ra^{1/4} \qquad 10^{4} < Ra < 10^{9} \tag{1.2}$$

Fujii et al. [21] developed a correlation for determining the Nusselt number in natural convection by the experimental study from a plate heated upwards to establish the relationship between heat flux and wall superheat. The correlation is shown as the heat flux against the superheat.

$$q" = 0.16\, k_l \left[\frac{g\beta}{\nu\alpha_l}\right]^{1/3} \Delta T^{4/3} \tag{1.3}$$

Based on scale analysis of cylindrical boundary layer equations, Yang [22] recommended including the length to diameter ratio in a dimensionless group for natural convective heat transfer from a slender cylinder. He suggests a universal correlation equation for both laminar and turbulent zones, which is as follows:

$$Nu = \left\{0.60\left(\frac{\mathrm{D}}{\mathrm{L}}\right)^{1/2} + 0.387\left[\frac{Ra}{\left[1+(0.492/\mathrm{Pr})^{9/16}\right]^{16/9}}\right]^{1/6}\right\}^2 \tag{1.4}$$

Numerous correlations have been presented after extensive studies on natural convection from a horizontal cylinder to determine the heat transfer coefficient. Churchill et al. [223 proposed a single correlation using various Rayleigh numbers as:

$$Nu = \left\{0.60 + \frac{0.387\, Ra^{1/6}}{\left[1+(0.599/Pr)^{9/16}\right]^{8/27}}\right\}^2 \tag{1.5}$$

Tsubouchi [24] presented a relationship for laminar natural convection over a range of Rayleigh numbers from 10^{-6} to 10^{-9}. The correlation is shown below:

$$Nu = 0.36 + 0.048\, Ra^{0.125} + 0.52\, Ra^{0.25} \tag{1.6}$$

Tadrist et al. [25] conducted an experiment on natural convection boiling to investigate the heat transfer in transition regime between natural convection and nucleate boiling. Therefore, they have compared the result with the correlation of Fujii et al. [21] described in Eq. (1.3).

Obtaining high-quality experimental data on natural convection heat transfer from slender tubes, specifically in water, is challenging. Fujii [26] conducted research on natural convection heat transfer from a vertical cylinder to water, measuring local heat transfer coefficients during laminar to turbulent flow transitions. "Quasi-steady state" was identified as similar to steady state in heat transfer coefficients.

Nucleate boiling heat transfer is analysed several times and multiple number of experiments have been done on it. This is the most important region amongst the four stages. Many studies have been done and some impressive results has come out. Rohsenow [27] developed generalized a heat transfer correlation for surface boiling in liquids which includes the surface effects.

$$q" = \mu_l h_{fg} \left[\frac{g(\rho_l - \rho_v)}{\sigma}\right]^{1/2} \left(\frac{c_{pl}\, \Delta T}{C_{sf} h_{fg} Pr_l^n}\right)^3 \tag{1.7}$$

The correlation has the arbitrary constant C_{sf} and the exponent n to account for the properties of the nucleation of any particular liquid-surface combination. They are determined experimentally.

There were some possibilities to modify the Rohsenow's [27] correlation. Pioro [28] had done the same. He modified the constant terms in Rohsenow's [27] correlation and expressed as:

$$\frac{h\, l^*}{k} = C_{sf}^* \left\{\frac{q"}{h_{fg} \rho_g^{0.5} [\sigma g(\rho_l - \rho_v)]^{0.25}}\right\}^{2/3} Pr^m \tag{1.8}$$

where C_{sf}^* is the constant, depended upon the nature of the heating surface–fluid combination and m is the power the properties of the nucleation.

Kruzhilin [29] suggested the correlation without making any specific efforts to consider the surface property, which is as follows:

$$\frac{h\, l^*}{k} = 0.082 \left(\frac{h_{fg} q"}{g(T_{sat})k} \frac{\rho_v}{(\rho_l - \rho_v)}\right)^{0.7} \left(\frac{T_{sat} c_{pl} \sigma \rho_l}{h_{fg}^2 \rho_v{}^2 D}\right)^{0.33} Pr^{-0.45} \tag{1.9}$$

Kutateladze et al. [30] simplified Kruzhilin's [29] correlation while sacrificing some accuracy and development developed a formula for heat transfer coefficient in boiling scenarios. In most of the cases, the latent heat of vaporization is one of the most important parameters in the correlation.

$$\frac{h\, l^*}{k} = 0.44 \left(\frac{10^{-4} q" p}{g h_{fg} \rho_v} \frac{\rho_l}{\rho_l - \rho_v}\right)^{0.7} Pr^{0.35} \tag{1.10}$$

Labuntsov [31] discovered the correlation that doesn't depend on the input of latent heat of vaporization. The correlation is expressed below in terms of the boiling heat transfer coefficient in nucleate boiling:

$$h = 0.075 \left[1 + 10\left(\frac{\rho_v}{(\rho_l - \rho_v)}\right)^{0.67}\right]\left(\frac{k^2}{\nu\sigma(T_{sat})}\right)^{0.33} q"^{0.67} \tag{1.11}$$

Mostinki [32] dismissed the surface effects and applied the principle for the respective states of pool boiling heat transfer and proposed a correlation including the reduced pressure and the critical pressure of the fluid.

$$h = 0.00417\, q"^{0.7} P_c^{0.69} F_{PF} \tag{1.12}$$

Where F_{PF} is a non-dimensional correction factor that characterizes the pressure effect on nucleate boiling.

A dynamic analysis of vapor bubbles was done by Foster, *et al.* [33], describing the nature of heat flux due to saturation pressure and temperature. The bubble radius and the bubble growth velocity hold important role here. They suggested the following correlation:

$$q" = 0.00122 \frac{k^{0.79} c_{pl}^{0.45} \rho_l^{0.49}}{\sigma^{0.5} \mu_l^{0.29} h_{fg}^{0.24} \rho_v^{0.24}} \Delta T^{1.24} \Delta P_{sat}^{0.75} \tag{1.13}$$

The most important feature of this correlation is supposed to be same for different types of fluids. The correlation holds an accuracy within ±30%.

Stephan, et al. [34] suggested four specific relationships utilizing a statistical multiple regression method for analysing water, refrigerants, organics, and cryogens. From those, the correlation for water is mentioned below:

$$h = 207 \left(\frac{k_l}{D_b}\right)\left(\frac{q" D_b}{k_l T_{sat}}\right)^{0.745} \left(\frac{\rho_v}{\rho_l}\right)^{0.581} Pr^{0.533} \tag{1.14}$$

The physical characteristics of the liquid are examined at the saturation temperature and therefore are considered to be. These correlations based on physical properties. They suggested the correlations for refrigerants whose average deviation was 10.6% within the decreased pressure range of 0.003-0.78.

Cooper [35] developed a precise correlation for predicting heat transfer in nucleate pool boiling by examining the relationship between heat transfer efficiency, heat flux, pressure, liquid molecular weight, and surface roughness. Increased roughness on a surface leads to higher nucleate boiling heat transfer. Surface roughness can be affected by fouling, corrosion, and oxidation.

$$h = 55.17 \left(\frac{P_{sat}}{P_c}\right)^{0.12-\ log_{10}\frac{Rp}{0.4}} \left(-log_{10}\frac{P_{sat}}{P_c}\right)^{-0.55} M^{-0.5} q"^{m} \quad (1.15)$$

Where m is an exponent use to compensate the relation between the heat flux and heat transfer coefficient.

Gorenflo [36] proposed a fluid-specific correlation for reduced pressure, impacting heat transfer coefficient during nucleate boiling. Surface texture, pressure, roughness, and temperature affect the flux calculation.

$$h = \ h_0\, F_{PF} \left(\frac{q"}{20000}\right)^{nf} Ra^{0.133} \quad (1.16)$$

Where nf is an exponent use to compensate the relation between the heat flux and heat transfer coefficient.

There are numerous number of experiments that describe the heat transfer in nucleate pool boiling. A recent experiment was done by Ciloglu [37] for nanofluids in hemispherical surface. Thus, the result of the experiment was compared with the most widely used nucleate boiling correlation of Rohsenow [27] described in Eq. (1.8).

Over the years, numerous researchers have tried to forecast CHF using different models and equations. A lot of these models have been proven to be lacking in completely capturing the essence of CHF, so a unified theory and governing equation still need to be developed. This shows how intricate the driving forces are in pool boiling events.

Kutateladze [38] suggested that the critical heat flux is caused by a hydrodynamic instability when the velocity of the vapour phase reaches a critical value. Following dimensional analysis, he suggested the correlation mentioned below:

$$q"_{CHF} = 0.16\ h_{fg}\rho_v^{1/2}[\sigma g(\rho_l - \rho_v)]^{1/4} \tag{1.17}$$

Rohsenow et al. [39] proposed that a higher amount of bubbles formed during high heat fluxes hinders the movement of liquid towards the heated surface. They suggested the following correlation:

$$q"_{CHF} = 0.012\ h_{fg}\rho_v \left(\frac{g_l}{g}\right)^{1/4} \left[\frac{\rho_l - \rho_v}{\rho_v}\right]^{0.6} \tag{1.18}$$

Zuber [40] suggested that as hydrodynamic critical heat flux is approached, instability occurs between the vapour flow moving away from the heated surface and the liquid towards the surface. He also proposed that vapour patches are created and destroyed on the heater's surface due to Taylor and Helmholtz instabilities being responsible for CHF. He devised a mathematical expression resembling Kutatelazde's [38] equation. This is the most widely used correlation proposed by him for horizontal surfaces of infinite extent. It is as follows:

$$q"_{CHF} = 0.131\ \rho_v h_{fg} \left[\frac{\sigma(\rho_l - \rho_v)g}{{\rho_v}^2}\right]^{1/4} \left(1 + \frac{\rho_v}{\rho_l}\right)^{1/4} \tag{1.19}$$

Critical heat flux has been analysed with some experiment keeping the surface roughness as the primary criteria. Ali [41] has investigated the same with an experiment and compared the results with some standard pool boiling correlations.

Transition boiling heat transfer occurs after the curve reached the CHF. The slope of the curve suddenly decreases. Till now, there are no such correlation perfectly describing the nature or behaviour or the rate of heat transfer in transition boiling regime.

The Leidenfrost point is the transition from unstable film boiling to the stable film boiling. It is the lower limit of film boiling heat transfer, where heat flux reaches the minimum value. Zuber [40] also derived the following correlation for calculating the minimum heat flux for a large horizontal plate:

$$q"_{min} = 0.09\ \rho_v h_{fg} \left[\frac{\sigma g(\rho_l - \rho_v)}{(\rho_l + \rho_v)^2}\right]^{1/4} \quad (1.20)$$

The effect and heat transfer in film boiling was analysed so many times by many researchers. This regime depends on the fluid used, surface geometry and some other conditions.

One of the most widely used correlation of pool boiling was proposed by Bromley [42]. He introduced an early concept for pool film boiling on outer surfaces utilizing Nusselt's film condensation theory and data gathered from experiments on tubes positioned horizontally. He expressed the heat transfer coefficient as:

$$h = C \left[\frac{g\rho_v h"_{fg} k_v^3 (\rho_l - \rho_v)}{\Delta T \mu_v D}\right]^{1/4} \quad (1.21)$$

Where, C= 0.62 for cylinder

C= 0.67 for sphere

And $$h"_{fg} = h_{fg} + 0.5\ c_{pv}(T_w - T_{sat}) \quad (1.22)$$

Over the years, there are extensive researches have been done based on the experiments of film boiling heat transfer for vertical surfaces [43-51] including vertical flat plates.

Correlations for estimating heat transfer are empirically derived from experimental data, with variables like surface geometry, fluid properties, and operating conditions influencing the selection. While helpful for estimation, accuracy varies, requiring validation with experimental data.

1.4. Organization of the Thesis

This thesis work is organized in such a manner that it contains the following chapters and covers the below topic for the purpose of fulfilling all the criteria for successful completion:

- **Introduction:** This chapter contains the following topics:

  - **Background:** It describes overview, importance and all the important phenomena related to the pool boiling heat transfer.

  - **Objective and Motivation:** The research gap containing existing methodologies and the motive and aim to solve the heat transfer problem related to pool boiling heat transfer.

  - **Literature Review:** The theoretical concepts, the previous and existing works, the experimental and analytical representations are shown here.

- **Scale Analysis of Pool Boiling and Film Boiling heat transfer:** The analytical approaches based on single phase natural convection, nucleate boiling and film boiling are shown here. Different methodologies to solve the heat transfer problem for pool boiling is also discussed here. The concept of non-dimensional parameters and the non-dimensionalization of the existing empirical correlation are done here. This segment also focuses on the different types of film boiling heat transfer over vertical surfaces.

- **Application of Artificial Neural Network on the pool boiling heat transfer:** The idea of the whole thesis work is to find out the pool boiling (especially nucleate boiling and film boiling) heat transfer computationally by using the ANN methodology. Thus, this chapter includes all the overview, importance and application of the ANN network in heat transfer domain. The problem solving approach using the ANN model is also discussed very firmly in this chapter.

- **Result and Discussion:** This is the most important chapter in the whole thesis work, where the outcomes from the ANN network have been shown and the discussions have been done on the prediction using the ANN model.

- **Result:** Feedforward ANN network is used in different types of pool boiling stages to find out the heat transfer in terms of Nusselt number. The outcomes from the simulation of the ANN network using different training algorithms for different conditions are shown in figure and table.

- **Discussion:** To put a clearer vision and compare the predicted result with the core experimental data and the existing empirical correlations with scale analysis, the outcomes are discussed to finalize the impact of ANN in pool boiling heat transfer.

- **Conclusion:** The whole thesis work is concluded in a manner such that the proper judgement for the solution methodology, outcomes from ANN, comparison with existing data and the application of the ANN in heat transfer field can be made. Also the future scope related to this thesis work is explained in this chapter.

- **References:** In this segment, the list of all sources cited in the work are mentioned. Those sources helped extremely in order to understand the problem, solution methodologies. Thus, the References give the credit to the original authors and researches, whose works are taken as consultants.

Chapter 2

Scale Analysis of Pool Boiling and Film Boiling heat transfer

The pool boiling regimes can be analyzed by some standard correlations. Natural convection boing and Nucleate boiling heat transfer have such correlations in huge numbers. But in order to analyze the Film boiling heat transfer, it was mentioned earlier that the unstable film boiling doesn't have such standard correlations that describe the nature of heat transfer in that zone. But stable film boiling can be analyzed non-dimensionally by scale analysis. Many previous works have been done to investigate and to get a clear picture of film boiling heat transfer. Scale analysis makes the heat transfer problems easier in order to get the rate of heat transfer, as the heat transfer equation are converted into Nusselt number correlation. It involves all the important properties of fluid and the conditions of heat transfer.

2.1. Dimensional Analysis of pool boiling and film boiling heat transfer

Scale analysis, also known as dimensional analysis or scaling analysis, is a technique utilized in physics, engineering, and applied mathematics to comprehend and simplify intricate systems by investigating the connections between variables and their measurement units. Scale analysis is based on the concept that many physical phenomena can be explained using fundamental dimensions like length, mass, time, temperature etc. Scale analysis aims to determine the main forces, parameters, or processes that control a system's behaviour by examining the dimensions and units of variables, eliminating the need to directly solve complicated equations.

The analysis focuses on verifying dimensional consistency in equations representing physical relationships. This includes verifying that all components in a mathematical expression possess identical units, aiding in the recognition of potential connections and interrelations. Non-dimensionalization is a process where variables are frequently represented using dimensionless parameters (like Reynolds number, Nusselt number, Jakob number etc.) that indicate proportions of important physical quantities. This makes the analysis easier and enables generalizations across various scales.

Scale analysis in fluid mechanics and heat transfer is employed to calculate dimensionless figures such as Reynolds number, which identify the flow regime (e.g., laminar or turbulent) by comparing inertial forces to viscous forces. Analysing scale assists in comprehending heat transfer processes and creating dimensionless ratios like the Nusselt number, which connects convective heat transfer with the fluid flow conditions and the geometry.

Thus the correlations got from many experimental and analytical result of pool boiling can be modified using scale analysis.

2.1.1. Scale Analysis of Single Phase Natural Convection

Natural convection boiling regimes can be understood by using the empirical correlations mention earlier in the Literature Review section. Each correlation can be converted in terms of non-dimensional heat transfer i.e., the Nusselt number (Nu) by using the heat flux or the heat transfer coefficient. One of the most popular natural convection boiling correlation was proposed by Fujii et al. [21], which is discussed earlier in Eq. (1.3). That correlation can be further non-dimensionalized. The average Nusselt number (Nu) vs. Rayleigh number (Ra) relation illustrates the heat-transfer coefficients results. The Nusselt number correlation is shown below:

Starting from the Eq. (1.3), it can be derived in a manner,

$$\left(\frac{q"}{\Delta T}\right)\left(\frac{1}{k_l}\right) = 0.16\ \left[\frac{g\beta\Delta T D^3}{\nu^2}\right]^{1/3}\left(\frac{1}{D}\right)\left(\frac{\nu}{\alpha}\right)^{1/3} \tag{2.1}$$

Or, $$\frac{h}{k_l}\,D = 0.16\ Gr^{1/3}Pr^{1/3} \tag{2.2}$$

Hence, $$Nu_{nc} = 0.16\ Ra^{1/3} \tag{2.3}$$

The above equation was derived by converting the heat flux term into Nusselt number (Nu) and by using the bubble diameter relationship, the other parameters are converted to Rayleigh number (Ra). This scale analysis indicates that the Nusselt number varies with the Rayleigh number (Ra) (which is the product of two other on-dimensional numbers, i.e. Grashof number (Gr) and Prandlt nimber (Pr)). From the above equation, it can be easily said that the correlation is valid for natural convection in single phase only. As the convection is due to the buoyancy force of the liquid, thus Rayleigh (Ra) number plays a significant role in order to obtain the heat transfer.

2.1.2. Scale Analysis of Nucleate Boiling

As same as the scale analysis of natural convection, the nucleate boiling correlations can also be obtained in non-dimensional form. The most widely used correlation for nucleate boiling, i.e., Rohsenow [27] correlation shown in Eq. (1.7) is also converted in non-dimensional equation by scale analysis. The above equation can be further non-dimensionalized and expressed in terms of Nusselt number, which is as follows:

Starting from the Eq. (1.7), it can be derived in a way,

$$\frac{q"}{\Delta T}\frac{1}{k_l} = \left(\frac{\mu_l c_{pl}}{k_l}\right)\left[\frac{g(\rho_l - \rho_v)}{\sigma}\right]^{1/2}\left(\frac{c_{pl}\,\Delta T}{C_{sf} h_{fg} Pr_l^n}\right)^3\left(\frac{h_{fg}}{c_{pl}\,\Delta T}\right) \tag{2.4}$$

$$\text{Or,} \quad \frac{h}{k_l}\,D = \left[\frac{Ja_{sup}}{C_{sf} Pr_l^n}\right]^3\left(\frac{Pr_l}{Ja_{sup}}\right)\frac{1}{D}\,D \tag{2.5}$$

$$\text{Hence,} \quad Nu_{nb} = \frac{(Ja_{sup}^2)(Pr_l^{1-3n})}{C_{sf}^3} \tag{2.6}$$

2.1.3. Scale Analysis of Film Boiling on vertical flat plate

Film boiling is a heat transfer process where a hot surface creates a vapour layer with a liquid, changing heat dynamics. The film boiling heat transfer is analysed using scale analysis multiple times. Das et al. conducted a scale analysis of film boiling using water on a vertical plate, simplifying the analysis by omitting vapour inertia and using a simplified radiation model. The Nusselt number equation for wall heat transfer was determined by a heat ratio criterion and the Grashof number to Reynolds number ratio. The research categorized wall superheats into high and low conditions, further classifying low superheats into natural and forced convection. The Nusselt number model showed strong predictive capability with over 96% alignment to experimental data. This analysis is also compared with some of the popular experiments [43-47] on film boiling over vertical surfaces. The models are written below as Nusselt number correlation which are used to calculate the heat transfer for the above condition:

A. High wall Superheat: There is a common correlation got from the scale analysis for film boiling over vertical flat plat for high wall superheat condition, which is shown below:

$$Nu_{hs} = \left[\left\{ \left(\frac{\left(3Re_l\left(\frac{v_v}{v_l}\right)Pr_v\right)}{Ra_v} \right)^2 + \left(\frac{12Ja_{sup}}{Ra_v}\right) \right\}^{\frac{1}{2}} - \left\{ \left(\frac{\left(3Re_l\left(\frac{v_v}{v_l}\right)Pr_v\right)}{Ra_v} \right) \right\} \right]^{-\frac{1}{2}} \tag{2.7}$$

B. Low wall Superheat: The conditions for low superheat is divided into two parts, which are:

a. Liquid-phase natural convection: The correlation for Nusselt number in this case can be written as:

$$Nu_{lsnc} = \frac{\mu_l}{\mu_v}\frac{Ja_{sub}}{Ja_{sup}}\frac{Pr_v}{Pr_l}Ra_l^{1/4} \tag{2.8}$$

b. Liquid-phase forced convection: The Nusselt number correlation derived for this condition is:

$$Nu_{lsfc} = \frac{\mu_l}{\mu_v}\frac{Ja_{sub}}{Ja_{sup}}\frac{Pr_v}{Pr_l^{2/3}}Re_l^{1/2} \tag{2.9}$$

Chapter 3

Application of Artificial Neural Network on the pool boiling heat transfer

An artificial neural network (ANN) is a group of basic interconnected algorithms that analyse data in order to react to external inputs. ANN attempts to mimic the functioning of the biological neural networks. Just as biological neural networks, consists of interconnected biological neurons, similarly, artificial neural networks feature interconnected artificial neurons across multiple layers, which with proper learning algorithms can produce accurate mapping of input/output data. There are several structures of ANNs. In a feedforward network, neurons of an input layer interact with one or subsequent multiple hidden layers which are eventually connected to an output layer. Each neuron receives signals from all the neurons of the previous layer weighed with suitable weights. The summation of these weighed inputs plus the bias for the neuron acts as the argument of the activation function of the particular neuron. The output of the neuron is the output of the activation function. Learning of the ANN is an optimisation problem which involves the alteration of the connection weights, to minimize a suitable error function. Several types of leaning algorithms like supervised and unsupervised learning are in practice [52]. A feedforward neural network with supervised learning can be used for modelling boiling heat transfer problems.

3.1. Basic ANN Structure

The organization of layers, neurons, and connections within an artificial neural network (ANN) is known as its structure [53]. The arrangement dictates the flow of information in the network and how it changes inputs to outputs. Here is a summary of the elements that determine the framework of an artificial feedforward neural network:

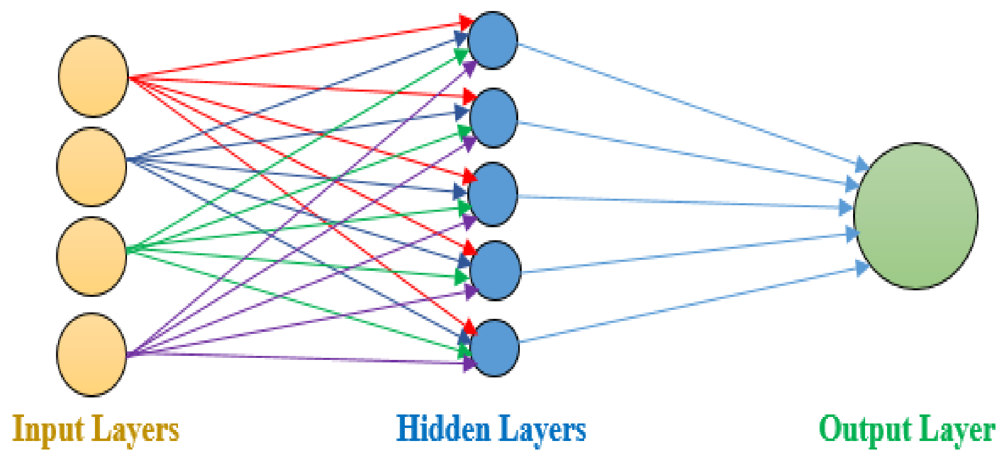


Fig. 3.1: A Basic structure of an Artificial Feedforward Neural Network

A. Input Layer

- The input layer is made up of neurons that receive the unprocessed input data. Every neuron represents a specific feature or input parameter [54].
- The input layer's quantity of neurons depends on the input data's dimension.

B. Hidden Layers

- Hidden layers consist of layers of neurons located between the input and output layers.
- Parameters like hidden layer quantity and neuron count can be adjusted based on problem complexity and resources [55].

C. Output Layer

- The final predictions or outputs of the network are generated by the output layer.
- The number of output neurons equals the number of inputs of the system [56].

3.2. General ANN Methodology

ANNs are a key element in contemporary machine learning and draw inspiration from the human brain's design and operations. Here is a typical approach for creating and implementing artificial neural networks (ANNs):

A. **Define the Problem:** Define the problem or goal for the network, such as classification, regression, clustering, or other specific tasks.

B. **Data collection and Pre-processing:** Gather relevant data on the topic, organizing it into tables or leaving it unstructured, cleaning and standardizing as necessary for analysis.

C. **Select a Network Architecture:** Choose the suitable neural network structure for your issue. Some of the most frequent categories are:
   - Feedforward Neural Networks (FNNs) [57]
   - Convolutional Neural Networks (CNNs) for image data
   - Recurrent Neural Networks (RNNs) for sequential data
   - Long Short-Term Memory networks (LSTMs) and Gated Recurrent Units (GRUs) for addressing the issue of disappearing gradients in recurrent neural networks (RNNs)
   - Transformer-based models used for processing tasks in natural language.

D. **Model Training:** Train a neural network using an optimization algorithm such as Bayesian Regularization, Levenberg-Marquardt, Gradient Descent, or variations like Adam or Root Mean Squared Propagation (RMSProp). The network adjusts weights and biases to minimize a loss function.

E. Validation: Assess trained model on validation set to check generalization and detect overfitting. Adjust hyper-parameters and model structure to improve performance.

F. Testing and Evaluation: Evaluate model on separate test set after performing well on validation set to ensure fair assessment of practical performance. Test set not used during training or validation.

G. Deployment and Monitoring: Utilize the model if it meets performance needs. Monitor real-world performance for quality decline, making adjustments as needed for optimization.

H. Iterate: Iterate on model, data pre-processing, and hyper-parameters in machine learning to enhance performance based on insights and feedback.

3.3. Selection of Hidden Neurons and Hidden Layers

Hidden neurons and layers are crucial in maintaining accuracy and shaping the architecture of Artificial Neural Networks (ANNs). The number of hidden neurons depends on inputs, training algorithms, and other parameters. Selecting the right number of hidden neurons [58] is vital for a successful network structure. There is no fixed rule for determining the ideal number of hidden neurons, as it varies based on the complexity of the problem. Starting with a small number of hidden neurons and gradually increasing them while monitoring performance can help identify the optimal point. Understanding the problem domain and the relationships between input and output variables can guide the decision on the number of hidden neurons. Larger datasets may require more complex models with more hidden neurons, while smaller datasets may benefit from simpler designs to prevent overfitting.

Selecting the appropriate number of hidden layers in an Artificial Neural Network (ANN) is crucial for creating an effective structure. While the number of neurons in a hidden layer may vary, the number of hidden layers significantly impacts the network's learning ability. Beginning with a single hidden layer is recommended to capture complex relationships and establish a performance foundation [59]. Deeper architectures are more effective for complex problems, with experimentation on a validation set helping determine the optimal depth. Finding the best architecture for optimal performance requires thorough testing and validation.

3.4. Solution Procedure

The solution process mainly distributed in three stages, which are:

- Training
- Validation
- Testing

3.4.1. Training

Training an Artificial Neural Network (ANN) for supervised learning requires modifying the network's weights and biases to reduce a specified loss function, thus enhancing the model's effectiveness in a particular activity. The model adopts the weights and biases and with a summation function, it initiates the training. After the function fitted properly, an activation function is loaded upon the adopted values of the inputs. In modern day, the most commonly and widely used activation functions are Rectified Linear Unit (ReLU) AND Sigmoid. After collecting the data and pre-processing, we need to go with the most suited algorithms to run the training problem. A simple schematic diagram of a feedforward ANN model with weight and bias is shown in Fig. 3.2.

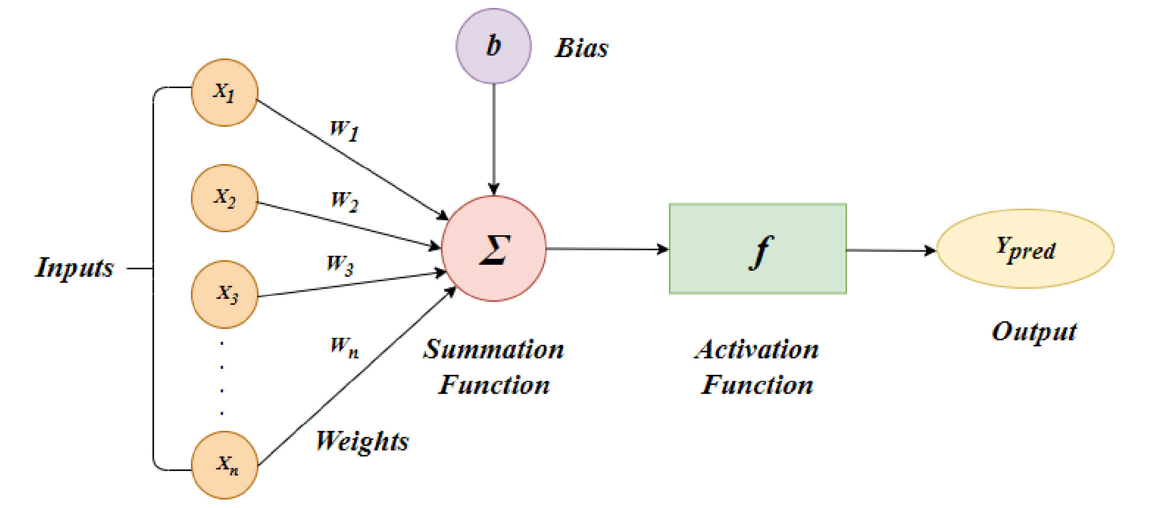


Fig. 3.2: Weight and Bias in a Feedforward ANN model

3.4.1.1. Training Algorithms

There are several algorithms generally used in ANN operation. In the whole thesis work, two types of training algorithms are used as they are familiar and most widely used. They are:

- Backpropagation Algorithm
- Bayesian Regularisation (BR)
- Levenberg-Marquardt (LM)

These algorithms are mainly chosen according to all the conditions and collections of dataset we have. The above two are described below:

A. Backpropagation Algorithm: Backpropagation is a technique used in artificial intelligence and machine learning to train neural networks by adjusting errors. The process involves computing the loss function, starting from output nodes and moving towards input nodes to minimize loss and achieve the desired outcome. It helps decrease errors and improve results in machine outputs by examining mistakes, matching them with expected outcomes, and iterating until the goal is reached [60].

There are two main types of backpropagation: Static backpropagation, used in feedforward neural networks to recognize characters and attributes, and recurrent, used in dynamic data sequences for tasks like sentiment analysis and speech recognition and Recurrent backpropagation, which allows data to flow in a feedback loop within hidden nodes, enabling the network to predict outcomes and recognize patterns in the data like the human brain learns by trial and error.

B. **Bayesian Neural Networks:** Bayesian neural networks (BNNs), also called Bayesian Regularization, are used in artificial neural networks (ANNs) to prevent overfitting and enhance generalization. In contrast to L1 or L2 regularization, which penalize big weights with a regularization term in the loss function, Bayesian Regularization views network weights as random variables and assigns a prior distribution to them. BRANNs, or Bayesian Regularized Artificial Neural Networks, are more resilient than traditional back-propagation neural networks, reducing the need for extensive cross-validation [61]. By transforming nonlinear regression into a statistically well-posed problem, BRANNs resemble ridge regression. These networks address challenges in Quantitative Structure-Activity Relationship (QSAR) modeling such as model selection, reliability, and validation effort [62]. They are resistant to overtraining and overfitting, using evidence procedures for objective Bayesian standards. BRANNs efficiently evaluate and train with various network parameters, deactivating unimportant weights. Additionally, Automatic Relevance Determination (ARD) can be applied to input variables in BRANNs, indicating the significance of each input and disregarding irrelevant or highly correlated indices [63]. This technique helps determine the most important variables for modeling activity data.

C. **Levenberg-Marquardt:** The Levenberg-Marquardt algorithm, frequently referred to as the damped least-squares technique, is a commonly utilized optimization method for training artificial neural networks (ANNs) [64]. It is especially favoured for teaching feedforward neural networks (FNNs) for regression tasks because of its efficiency and effectiveness in reducing the mean squared error (MSE) loss function [65]. The Levenberg-Marquardt algorithm provides a numeric solution for reducing nonlinear functions with reliable convergence. Ideal for small to medium-sized artificial neural network problems, it merges the steepest descent and Gauss-Newton methods. This algorithm retains the speed benefits of Gauss-Newton and reliability of steepest descent, excelling in complex error surfaces. While slower than Gauss-Newton, it converges faster than steepest descent [66]. By utilizing a dual training approach, it first relies on steepest descent in areas with complex curvature before transitioning to Gauss-Newton for quicker convergence. Ultimately, the Levenberg-Marquardt algorithm is a powerful tool for optimizing neural networks with varying levels of complexity.

3.4.1.2. Weights and Biases

Weights regulate the intensity of links among neurons and represent associations among input characteristics and desired results. They determine signal strength in neurons, affecting input data influence on output. Biases help neurons be adaptable and flexible, enabling them to activate based on different input circumstances. That means, Biases add characteristics with a value of 1 to the neural network for efficient propagation forward [67].

3.4.1.3. Summation Functions

The purpose of the summation function is to connect the weights and inputs and compute their total. The summed up data further goes for the activation through Activation functions.

3.4.1.4. Activation Functions

The activation function determines if a neuron should be activated by computing the weighted sum and then adding bias to the result. The activation function's purpose is to add non-linearity to the neuron's output. This implies that it will determine the significance of the neuron's input to the network during prediction by utilizing basic mathematical operations [68]. Some of the common activation functions are: Linear or Identity Activation Function, Non-linear Activation Function, Sigmoid or Logistic Activation Function, Tanh or hyperbolic tangent Activation Function, ReLU (Rectified Linear Unit) Activation Function, Leaky ReLU etc.

The input layer simply contains the input data without conducting any calculations. Hence, no activation function is utilized in that case. A non-linear activation function is necessary for hidden layers in a neural network. This is necessary for incorporating non-linear elements into the network in order for it to learn the complex patterns. As none of our output is negative as per the source data, thus, we have used the ReLU activation function in the hidden layers.

3.4.2. Validation

Validation set is used to monitor the learning and to prevent the overfitting in training process. Cross-validation involves dividing data into k folds for testing and training to reduce performance estimate variance and enhance data utilization. A more dependable assessment of ANN algorithm effectiveness is achieved by calculating performance metrics across folds. This method can also help in comparing and choosing the optimal ANN models or designs for the particular issue being addressed [69]. Thus, the separated data for validation can be validated by using ANN model with the same network.

3.4.3. Testing

After the training and validation are done, then the main task is to test the samples which were not involved in the network during training. Using the same training algorithm and the same number of hidden neurons, the testing should be done with the same function fitted neural network. In this case, the number of input variables should be as same as the training variables. The testing will be done computationally. It can be done either by "MATLAB-Simulink" or the "MATLAB Code" for implementing ANN. The data enlisted for testing will be done in order to compare the results of existing methods. The test would be chosen as more accurate than the scale analysis if the statistical analysis stands with the ANN prediction.

For function fitted neural network, the training, validation and testing samples can be distinguished in a percentage form as 70, 10 and 20% respectively. But for the coded network, the training and testing can be distributed as nearly 70% and 30% respectively for all the problems chosen for prediction.

3.5. Current Problem Architecture

Artificial Neural Network has been used multiple times in the field of heat transfer consisting many boiling heat transfer problems [70-72]. ANN model is used in the thesis work to predict the heat transfer of different stages of pool boiling and film boiling of vertical plate under different conditions. Every stages are oriented with specific feedforward ANN models using different algorithms and different number of hidden neurons in order to get the accurate predicted result than the scaled data comparing with the experimental results. So, different types of network architecture are created for different conditions. The algorithms and number of algorithms are adjusted according to the conditions. The configuration varies with the number of samples, variation of inputs etc. The most fitted architecture for each conditions are found by applying different ANN models for numerous times. The selection of the inputs was quite challenging, which was overcome by selecting different non-dimensional parameters. The parametric analysis is done based on the condition sated in the experiments for different regimes. The whole procedure of training, testing and validation involves the "MATLAB" for simulation of the heat transfer problems. MATLAB provides resources for machine learning, deep learning, and data analytics, allowing for the creation and implementation of algorithms in these areas. Thus, by using the training algorithms in MATLAB, we can have the simulation for training and testing. The features of the most suitable training algorithms are discussed earlier. The structure of any ANN model in this work is defined by "Training Algorithm-Number of Hidden Neurons". For training the ANN model, the sources of training data are taken from several boiling heat transfer experiments.

3.5.1. Network for Single Phase Natural Convection

The experiment of Tadrist et al. [25] is taken as the source of the training data, where due to domination of the buoyancy force, Rayleigh number comes in action for single phase natural convection. Thus, Rayleigh numbers are taken as the inputs for single phase natural convection. To get more accurate value of Nusselt number than the scale analysis, this condition is processed for multiple times. The best outcomes for the above mentioned condition has come out to be "LM-5" (means Levenberg-Marquardt algorithm is used for training the problem with using 10 hidden neurons). The Rayleigh numbers got from the experimental data is taken as input of ANN and Nusselt numbers are taken as output of ANN. Hence, randomly selected samples of 70% are taken for training of our problem and 30% of the overall data are taken for the testing. Then the simulation has been done several times and with using the best training format of ANN, the rest of those 30% samples are tested. Thus, as a result, ANN has given different Nusselt numbers for different Rayleigh numbers.

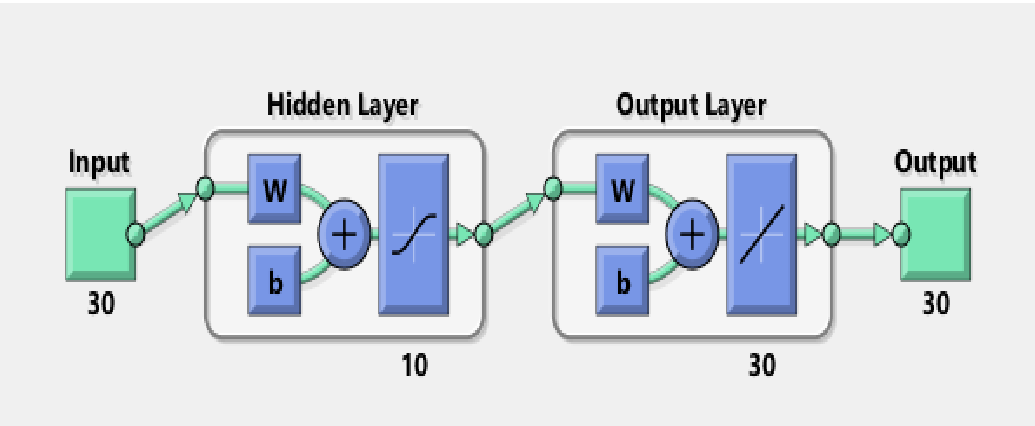


Fig. 3.3:- A basic schematic topology of Feedforward ANN model for predicting the Nusselt number for Single phase Natural convection

3.5.2. Network for Nucleate Boiling

The Ciloglu [37] is taken as the source of training data. Nucleate boiling heat transfer is influenced by the Jakob number and the Prandlt number. The Prandlt number is constant (1.863) for the reference taken for ANN modelling. So, Jakob number is taken as the input of the architecture. The inputs for this condition are very small ranging from 0.02 to 0.038. Thus, the design of the network was a challenging task. “LM-10” was fitted as the most accurate network for predicting the output, i.e., the Nusselt number. After getting the non-dimensional parameters, the Jakob number for superheating condition is taken as the input and the Nusselt numbers are taken as the output. The modified data are divided into two parts as same as the previous result, i.e., 70% of the prior data is taken for training and the rest of the 30% data are taken for testing of the network.

3.5.3. Network for Film boiling on vertical flat plate

Several experiments [43-47] on film boiling over vertical surfaces are taken as the sources of training data. Film boiling over vertical flat plate was performed by the scale analysis [19]. But seeing the outcomes of the scale analysis, the ANN model is predicting Nusselt number as the result. Film boiling over a vertical surface has different condition of superheating, phases and convection involvement. Thus, a same training algorithm is not applicable for all the conditions. The conditions for film boiling is mentioned earlier. Four non-dimensional parameters are taken as the inputs of the ANN model for film boiling. They are Ja_{sup}, Ja_{sub}, Re_l and Gr_v. For different values of the inputs, the Nusselt number varies differently. As the above four parameters have some influence on the film boiling, thus they are taken as input of the ANN network. The data is split into two portions just like before, with 70% used for training and the remaining 30% used for testing the network. After simulating numerous times, the proper training algorithm and the number of hidden neurons which should be used for the film boiling has come out. A brief description of the network architecture for different conditions of film boiling are mentioned below:

A. **Network for High wall superheat:** It is initiated with "BR-10" configuration as the condition is most suited for implementing the algorithms and the number of hidden neurons.

B. **Network for Low wall superheat:** Both of the conditions for low wall superheat was analyzed by ANN model using the model configuration of "BR-15".

For the modeling, the main challenge was to define a proper ANN network architecture by choosing most suitable algorithm, proper amount of hidden neuron, exact activation functions for the hidden layers and the output layer for the training. As the same configurations would be applied while testing the separated data, the training is an important task. The below tables describes that how the training is categorized in order to solve the chosen problem for pool boiling heat transfer by using the Artificial Neural Network. The predictions are done on the basis of the enlisted data set by distributing them as the training and testing dataset. Table 3.1 narrates about the chosen activation layers and their functional form for the modelling. As the range of output data varies above the zero and subsequently the belong to same genus, the same activation layers are used for all the four problems. Table 3.2 describes how the arrangements are done for the chosen problems.

Table 3.1: Details of the chosen Activation Functions

Name of the Layer	Name of the Activation Function	Equation of the Activation Function
Hidden Layers	ReLU	$f(x) = max(0, x)$
Output Layer	Linear	$f(x) = x$

For the above table, x is the weighted input for training, i.e., Weight * Input + Bias.

Table 3.2: ANN model framework used in current problem						
Sl. No.	**Problem**	**Input Variables**	**No. of Input Samples**	**No. of Hidden Neurons**	**Training Algorithm**	**Output Variable**
1	Pool Boiling Natural Convection	Ra	44	5	LM	Nu_{nc}
2	Pool Nucleate Boiling	Ja_{sup}	43	10	LM	Nu_{nb}
3	Film Boiling over Vertical Flat Plate – High Superheat	Ja_{sup}, Ja_{sub}, Re_l and Gr_v	61	10	BR	Nu_{hs}
4	Film Boiling over Vertical Flat Plate – Low Superheat	Ja_{sup}, Ja_{sub}, Re_l and Gr_v	43	15	BR	Nu_{ls}

Chapter 4

Result and Discussion

The above solution methods are used to obtain the Nusselt number in different pool boiling regimes for different conditions. The network framework is organized by doing the training until it gives the best result for the test data. The information provided in the previous chapter helped to choose the proper networks for every problem. The results are also compared to the most accurate correlations which are either widely used in the field of heat transfer or useful to determine the rate of heat transfer. Depending upon our problems mentioned earlier, we have to use the ANN tool with different parameters and algorithms. After running the codes for several times until we got the best results, we have got the ANN results for testing samples.

These results are examined for the above three regimes of pool boiling, for the correlations have been proposed. For every time, the ANN methodology have been applied to get the result for heat transfer. The primary comparison for any analysis is done on the basis of the Mean Squared Error (MSE) amongst all the observations. The general formula for calculating the MSE is:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (Experimental\ Value - Predicted\ ANN\ Result)^2 \qquad (4.1)$$

Where N is the number of observations and the Σ indicates that a summation is performed over all values of i.

The maximum percentage error is also calculated in order to see the range of errors for both the scale analysis and ANN prediction.

4.1. Results for Single Phase Natural Convection

The beginning of the analysis was started with examining the Natural convection boiling. The data samples extracted from an experimental analysis of Tadrist et al. [25] and then examined by the Artificial Neural Network. Basically, Feedforward Neural Network is used to run the problem.

So, to simulate the ANN tool, at first the overall data are collected from the comparison curve for experimental and result from scale analysis of the correlation of Fujii et al. [21] shown in Eq. (2.3). Both of the extracted data is first non-dimensionalized in terms of Rayleigh number and Nusselt number using the properties of the fluid used at stipulated conditions. Then the modelling was started with the training. The prediction is done with 20 Epochs. After running the model, it gives the MSE and Regression value, which are shown in Table 4.1.

Table 4.1: Result for various operations for ANN modelling

Name of the Operation	MSE	Regression
Training	0.0034	0.9999
Validation	0.0049	0.9899
Testing	0.0093	0.9687

The above table shows the representation of the MSE and Regression for the problem of single phase natural convection by the ANN modelling. Clearly it is showing that the regression line is very close to the set of existing data points, which is the desired Nusselt number. The table is an example for variation of results for ANN modelling in case of single phase natural convection.

The obtained result by ANN prediction is collected and then compared with the experimental data and the results from the scale analysis. The comparison is shown via Fig. 4.1 below.

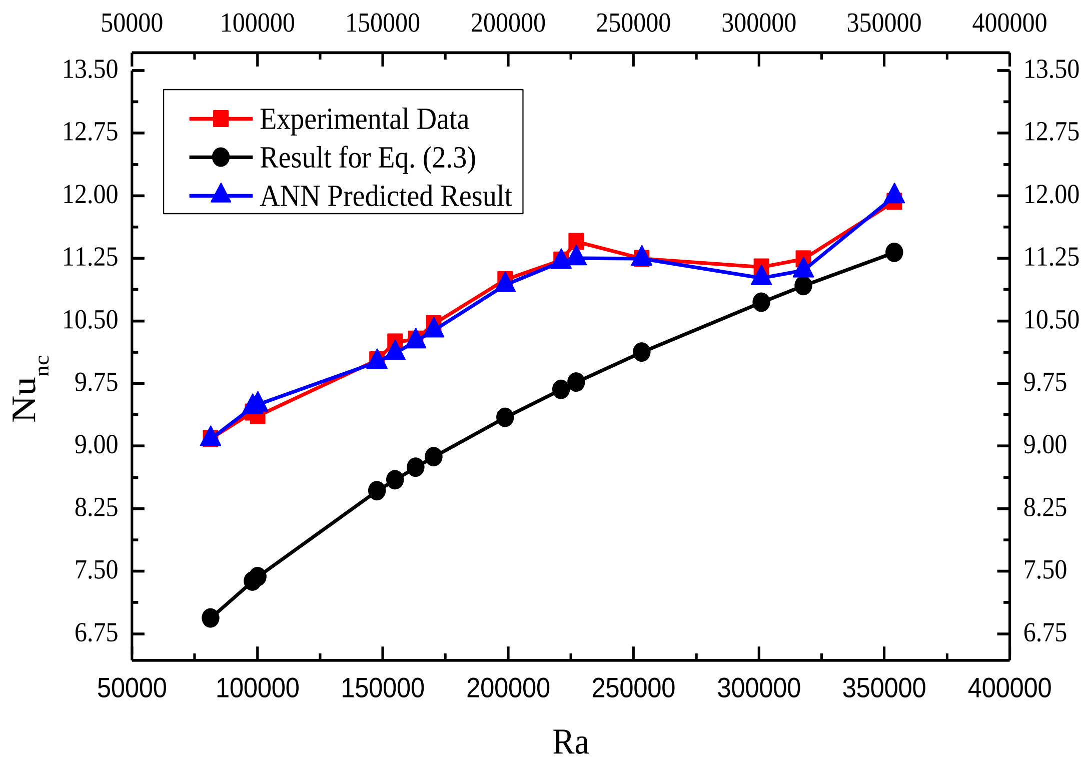


Fig. 4.1: Comparison Curve of Nusselt number vs Rayleigh number for Experimental data, Result of Eq. (2.3) and ANN predicted result for Single phase Natural convection

The above figure shows that the values of Nusselt number is varying with different Rayleigh numbers for all the three curves. It clearly shows that the results obtained from the ANN analysis are more accurate than the results of scale analysis for the empirical correlation of Fujii et al. [21] from Eq. (2.3) comparing with the experimental results of Tadrist et al. [25]. In order to compare them statistically, the MSE and the Maximum Percentage Error have been calculated. The MSE of the scale analysis has come out to be 2.3159, whereas the MSE of the ANN result is 0.0093. The maximum percentage error for the above two conditions are 23.68 and 1.74 respectively. The error band for ANN predicted result shows a great outcome which is favorable for the thesis. All of the samples chosen for testing lies within the error range of 2%. Thus for the natural convection boiling zone can be simulated using ANN and it gives more accurate value of the output, i.e., Nusselt number compared to the empirical correlation.

4.2. Results for Nucleate Boiling

Nucleate boiling heat transfer is also analyzed as the natural convection boiling. The process of ANN simulation is applied to get the result. The experiment of Ciloglu [37] of nucleate pool boiling of a nanofluid from a hemispherical surface is taken as the reference. The whole experiment was done using Deionized water (DI water). To compare the result, the most widely used nucleate pool boiling correlation, i.e., the Rohsenow [27] correlation has been non-dimensionalized to get the fluid independent properties using scale analysis, which is shown in Eq. (2.6). All the constant properties are taken as mentioned in the experiment. Then the modelling was started with the training. The prediction is done with 25 Epochs.Thus, the test result is obtained from ANN modelling and compared with the experimental results and the results from scale analysis. The comparison is shown by the Fig. 4.2.

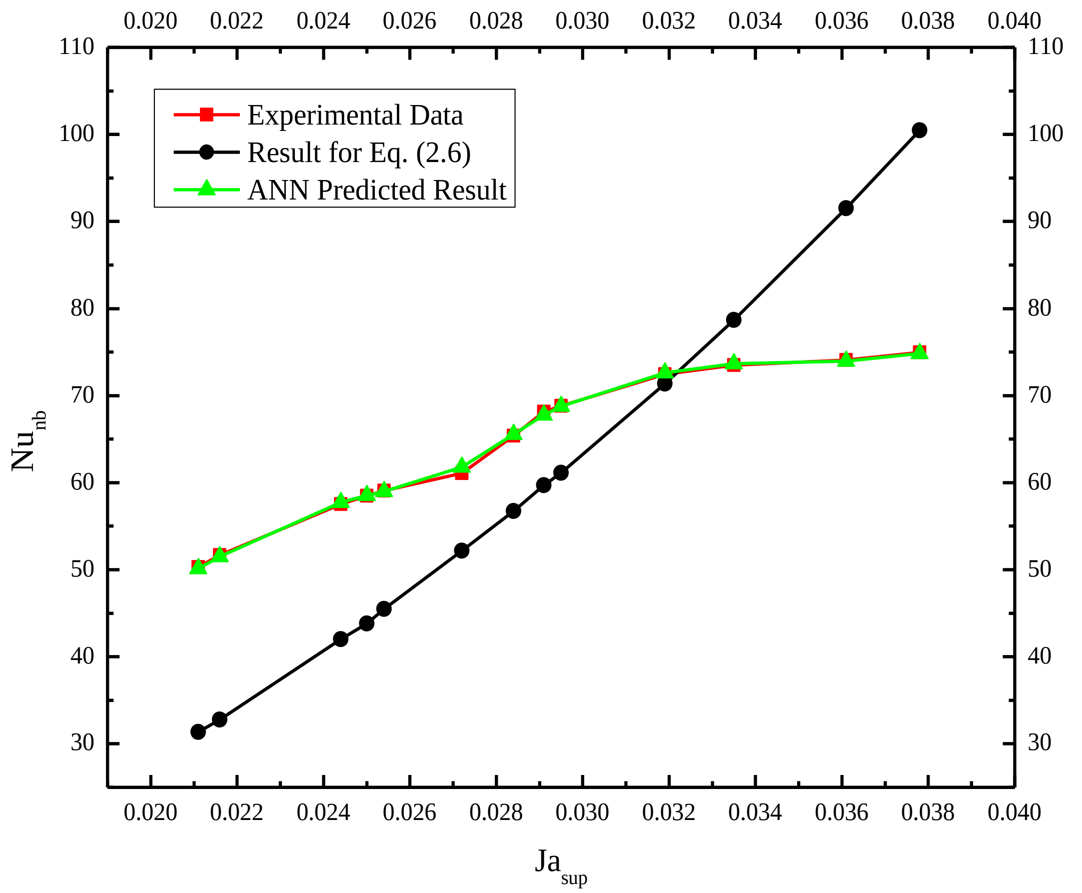


Fig. 4.2: Comparison Curve of Nusselt number vs Jakob number for Experimental data, Result of Eq. (2.6) and ANN predicted result for Nucleate boiling for DI water

The figure above demonstrates how the Nusselt number values change with varying Jakob numbers on all three curves. The results from the ANN analysis are evidently more precise than the results of the scale analysis for Rohsenow's [27] empirical correlation from Eq. 20. (2.7) in comparison with the findings of Ciloglu [37]. The MSE and Maximum Percentage Error were calculated for statistical comparison. The MSE of scale analysis is 202.0126, while the ANN result has an MSE of 0.0706. This is a huge variation in terms of correctness. The highest percentage error for the two conditions mentioned above is 37.64 and 1.17, respectively. The error range of the ANN prediction results demonstrates a positive outcome that supports the thesis. All the selected samples for testing fall within a margin of error of 2%. Therefore, the nucleate boiling zone can be replicated using artificial neural networks, providing more precise results for the Nusselt number compared to the empirical correlation.

4.3. Result for Film Boiling over a Vertical Flat Plate

Film boiling over vertical plate has numerous number of experiments those are analyzed to understand the heat transfer in this boiling region. The experiments [43-47] are taken for training the network and to predict the heat transfer. The comparison of the experiment with the scale analysis and the ANN prediction is also done in this segment. The experiments are separated and thus the predictions are performed. Each of the predictions contains four inputs as Ja_{sup}, Ja_{sub}, Re_l and Gr_v. The outputs of the predictions are the Nusselt number for convective heat transfer. To calculate the total heat transfer for film boiling, a standard correlation is used to obtained the radiative Nusselt number and then it was added with the convective heat transfer with another correlation. The correlations are:

$$Nu_{rad} = \left\{\varepsilon_{eq}\sigma(T_{wall}^4 - T_{sat}^4)/(T_{wall} - T_{sat})\right\}L_c/k_v \tag{4.2}$$

Where $$\varepsilon_{eq} = \left(\frac{1}{\varepsilon_{eq}} + \frac{1}{\varepsilon_{eq}} - 1\right)^{-1} \tag{4.3}$$

And $$Nu_{expt,total} = Nu_{expt,conv} + \frac{3}{4}\,Nu_{rad} \tag{4.4}$$

Thus, the result of the thesis work is divided into two major parts. These are discussed below:

4.3.1. Result for High wall Superheated Film Boiling

This observation is taken for negligible forced convection and the subcooling of water is characterized by zero Re_l and Ja_{sub}. Thus, the results of the experiments are taken for predicting the Nusselt number. Several experiments are taken to perform the ANN prediction. Then the modelling was started with the training. The prediction is done with 40 Epochs. Each of the parameters are analyzed, tested and compared with the existing experimental data and the equation of scale analysis [19] which is shown in Eq. (2.7).

4.3.1.1. Film boiling of Saturated water under Natural convection

A greater Jakob number indicates increased thermal resistance at the wall due to a reduced Nusselt number. This is due to the formation of a thicker layer of vapour over a wall that is hotter. Thus the variation of the Nusselt number is analyzed with the Ja_{sup}. From the bunch of experiments on film boiling over vertical surfaces, two experiments are taken as the problems to solve the heat transfer with ANN model for the high-superheat film boiling of liquid water at saturated condition under the natural convection.

A. **Prediction Film boiling for Vertical cylinder:** The experiment from Shiotsu et al. [43] is taken as the reference in order to solve the problem. Heat transfer in film boiling from a vertical cylinder is studied under forced flow of liquids, at both saturated and subcooled conditions, and various pressures. This experiment was performed at 2.94 bar pressure for boiling of water over vertical cylinder. So far the best result had come and the Nusselt number came out in a more accurate manner than the scaled data. The inputs and outputs are shown below in a table form to visualise the comparison amongst total experimental Nusselt number, total scaled Nusselt number and the total ANN Nusselt number:

Table 4.2: Comparison table for the total Nusselt number of experiment, scale and ANN prediction for high wall superheat and saturated water under natural convection for vertical cylinder							
Sl. No.	Ja_{sup}	Ja_{sub}	Re_l	Gr_v	$Nu_{expt,tot}$	$Nu_{scale,tot}$	$Nu_{ann,tot}$
1	0.118	0	0	685000	22.955	25.085	21.167
2	0.155	0	0	591000	19.785	22.575	19.312
3	0.198	0	0	505000	17.455	20.375	17.604
4	0.273	0	0	386000	15.45	17.65	15.545
5	0.31	0	0	344000	14.96	16.65	14.818
6	0.345	0	0	312000	14.5	15.85	14.274

The above samples shown in the above table are some of the selected tested data for ANN prediction. The prediction got the impressive results as the outcomes from ANN network got way more accuracy than the scaled data, which can be clearly visible. Though the actual statistical comparison would give more clearance to the analysis. The MSE for the scaled data has come out to be 5.9210**,** whereas the MSE for the ANN predicted result is 0.2828, which is way better than the scaled result. The maximum percentage errors for each of the previous case is 16.72 and 7.86 respectively. Also most of the results i.e., 83% from ANN prediction lie within an error band of 3%. The above statistical comparison shows that the accuracy of ANN prediction for the stated condition is far better than the scaled data comparing with the experimental results.

B. **Prediction of Film boiling for Vertical plate:** The experiment of Vijaykumar et al. [44] is also taken as another reference for solving the problem on film boiling heat transfer. A study was conducted on subcooled film boiling on a vertical surface, insights on hydrodynamics. This time, the experiment was performed at atmospheric pressure for boiling of water. The best result so far was obtained by accurately calculating the Nusselt number, compared to the scaled data. The table below shows inputs and outputs to visually compare experimental, scaled, and ANN Nusselt numbers.

Table 4.3: Comparison table for the total Nusselt number of experiment, scale and ANN prediction for high wall superheat and saturated water natural convection for vertical plate							
Sl. No.	Ja_{sup}	Ja_{sub}	Re_l	Gr_v	$Nu_{expt,tot}$	$Nu_{scale,tot}$	$Nu_{ann,tot}$
1	0.131	0	0	310000	18.705	20.075	18.945
2	0.131	0.003	0	310000	22.345	20.075	22.935
3	0.131	0.0148	0	312000	18.705	20.075	17.245
4	0.174	0	0	258000	16.975	17.775	17.257
5	0.174	0.0046	0	258000	20.455	17.775	21.462
6	0.263	0	0	184000	13.615	14.775	15.158

The samples displayed in the table above are chosen test data used for predicting with ANN. The forecast showed excellent results as the outcomes obtained from the ANN network were more accurate than those from the scaled data, making it easily noticeable. Although conducting an actual statistical comparison would provide further clarity for the analysis. The scaled data produced an MSE of 2.7487, while the ANN predicted result had an MSE of 1.3999, which is significantly superior to the scaled result. The highest percent errors for all of the prior scenarios is 13.10 and 12.26 respectively. Additionally, a majority of the outcomes, specifically 57% from artificial neural network forecasting, fall within a 5% margin of error. The statistical analysis above indicates that the accuracy of the ANN prediction for the specified condition is significantly superior to that of the scaled data when compared to the experimental results.

4.3.1.2. Film Boiling of Water under Low subcooling and Natural convection

Film boiling for the low subcooling natural convection is taken to analyse and to predict the heat transfer for high-superheat condition. It is also done as same as the previous two experiments in terms of calculating the Nusselt number by ANN prediction.

An experiment of Okkonen et al. [45] is taken in order to solve the problem on film boiling heat transfer for long vertical surfaces. The above research compares the anticipated heat transfer properties with experimental findings in a high wall temperature range of 600–1200 °C and stagnant water with minimal subcooling of just 3 °C. So far, the best result was obtained by accurately calculating the Nusselt number compared to the scaled data. The information provided in the table allows for a visual comparison of the total experimental, total scaled and total ANN predicted Nusselt number.

Table 4.4: Comparison table for the total Nusselt number of experiment, scale and ANN prediction for high wall superheat under low subcooling of water and natural convection for long vertical surface

Sl. No.	Ja_{sup}	Ja_{sub}	Re_l	Gr_v	$Nu_{expt,tot}$	$Nu_{scale,tot}$	$Nu_{ann,tot}$
1	0.437	0.0056	0	106000	14.27	13.55	14.773
2	0.532	0.0056	0	83100	14.315	12.775	13.995
3	0.645	0.0056	0	63300	12.81	12.2	13.344
4	0.778	0.0056	0	48400	12.705	11.725	12.838
5	0.856	0.0056	0	41700	12.815	11.675	12.663
6	1.058	0.0056	0	30000	13.645	11.725	12.504

The test data selected for prediction with ANN is shown in the table above. The prediction had great outcomes because the results from the ANN network were more precise compared to the ones from the scaled data, which was easily noticeable. While carrying out a real statistical comparison would offer more clarity for the analysis. The rescaled data yielded an MSE of 1.5347, whereas the ANN predicted outcome obtained an MSE of 0.3305, proving to be notably better than the rescaled outcome. The greatest percentage deviations observed in previous situations are 14.07 and 8.35, in that order.

Moreover, most of the results, specifically 83.33% from predicting with artificial neural networks, are within a 5% margin of error. The statistical analysis shows that the accuracy of the ANN prediction for the specified condition is much better than that of the scaled data in comparison to the experimental results.

4.3.1.3. Film boiling for Mixed water convection

To predict the heat transfer in high superheat and mixed water convection, two experiments are taken, where liquid Reynolds numbers have a high range value. In these two cases, the variation of Nusselt number occurs significantly which changing of the Reynolds number. Both the model and the experiments have successfully captured the increase in wall heat transfer with a higher far-stream Reynolds number, which is physically feasible. The significant range of Reynolds numbers shows a major difference in the Nusselt number coefficient, which may be due to the unstable liquid-vapour interfacial wave.

A. **Prediction of Film boiling for Vertical flat plate:** The experiment of Meduri et al. [46] is taken as the reference for the prediction of Nusselt number by using ANN network. The experiment was done on Partitioning of wall heat flux throughout subcooled forced flow film boiling of water on a vertical surface. The experiment Data were collected for mass fluxes varying from 0 to 700 kg/m^{2}s, inlet subcoolings varying from 0 to 25 °C, and wall superheats varying from 200 to 400 °C. Up to this point, the most successful outcome was achieved through precise computation of the Nusselt number when compared to the normalized data. The table presents a way to visually compare the Nusselt number values from experimental, scaled, and ANN predicted data.

Table 4.5: Comparison table for the total Nusselt number of experiment, scale and ANN prediction for high wall superheat and mixed water convection for vertical flat plate							
Sl. No.	Ja_{sup}	Ja_{sub}	Re_l	Gr_v	$Nu_{expt,tot}$	$Nu_{scale,tot}$	$Nu_{ann,tot}$
1	0.174	0.0005	2969	259000	18.955	18.775	18.885
2	0.236	0.0006	2969	204000	17.485	16.175	16.839
3	0.263	0.0014	2970	185000	16.075	15.375	16.173
4	0.308	0.0011	2967	157000	14.625	14.175	15.061

The table above displays the test data chosen for prediction using ANN. The forecast was successful as the ANN network produced more accurate results than the scaled data, which was easily discernible. Conducting an actual statistical comparison would provide greater clarity for the analysis. The rescaled data had an MSE of 0.6102, while the ANN predicted outcome had a much lower MSE of 0.1555, demonstrating a significant improvement over the rescaled result. The highest percentage variances noted in earlier cases are 7.49 and 3.69, respectively. Additionally, the majority of the outcomes, a precise 100% when using artificial neural networks for prediction, fall within a margin of error of 4%. The statistical analysis indicates that the ANN prediction's accuracy for the specified condition significantly outperforms the scaled data when compared to the experimental results.

B. **Prediction of Film boiling for Vertical cylinder:** The experiment of Shiotsu et al [43] for film boiling from a vertical cylinder is taken another time as a reference to get the better outcomes for ANN prediction over scaled data. But this time, the condition is for mixed convection. Until now, the best result was obtained by accurately calculating the Nusselt number in comparison with the normalized data. The table illustrates a method to visually compare few samples of Nusselt number values obtained from experimental, scaled, and ANN predicted data.

Table 4.6: Comparison table for the total Nusselt number of experiment, scale and ANN prediction for high superheat and mixed water convection for a vertical cylinder							
Sl. No.	Ja_{sup}	Ja_{sub}	Re_l	Gr_v	$Nu_{expt,tot}$	$Nu_{scale,tot}$	$Nu_{ann,tot}$
1	0.167	0	17812	560000	26.045	31.875	26.523
2	0.197	0	28435	505000	33.885	33.975	33.116
3	0.207	0	24894	487000	29.045	31.275	29.501
4	0.235	0	28435	440000	30.705	30.075	30.674
5	0.273	0	28435	386000	28.3	27.15	28.449
6	0.316	0	17812	344000	18.58	21.55	18.945
7	0.35	0	28435	306000	24.52	22.85	24.522
8	0.424	0	24894	250000	19.89	19.15	19.585
9	0.436	0	17812	242000	15.56	17.35	15.765
10	0.477	0	28435	228000	20.19	18.55	20.410

The test data selected for prediction using ANN is shown in the table above. The prediction was accurate with the ANN network delivering more precise outcomes compared to the scaled data, which was clearly noticeable. Performing a real statistical comparison would offer more clarity for the evaluation. The rescaled data had an MSE of 5.9210, whereas the ANN predicted outcome showed a considerably lower MSE of 0.2828, indicating a marked enhancement over the rescaled outcome. The previous cases showed the biggest deviations with percentages of 22.38 and 2.84. Furthermore, when utilizing artificial neural networks for forecasting, all the results are accurate within a 3% margin of error. The statistical analysis shows that the accuracy of the ANN prediction is much better than the scaled data in comparison to the experimental results for the specified condition.

4.3.2. Result for Low wall superheated Film Boiling

The low wall superheat condition is divided into two parts for a comprehensive analysis. Both of the conditions are trained with the same network. In both of the cases, the network architecture for modelling remains the same. Then the modelling was started with the training. The prediction is done with 50 Epochs.

4.3.2.1. Film boiling of Natural Liquid-phase convection

For the prediction of Nusselt number using ANN model for low wall superheat and natural convection for liquid phase, the experiment of Okkonen et al. [45] is taken again as a reference. After applying the ANN network on the input parameters, the value of Nusselt numbers have come out as an impressive outcome. The information provided in the table allows for a visual comparison of few samples of the total experimental data, total scaled result from Eq. (2.8) and total ANN predicted Nusselt number.

Table 4.7: Comparison table for the total Nusselt number of experiment, scale and ANN prediction for low superheat and natural liquid-phase convection for a long vertical surface

Sl. No.	Ja_{sup}	Ja_{sub}	Re_l	Gr_v	$Nu_{expt,tot}$	$Nu_{scale,tot}$	$Nu_{ann,tot}$
1	0.524	0.0776	0	83200	23.200	28.140	25.667
2	0.529	0.0776	0	82100	22.169	27.779	25.524
3	0.944	0.05	0	35600	15.817	8.457	16.334
4	0.945	0.0776	0	35500	17.329	12.869	18.311
5	1.001	0.1071	0	32400	19.142	16.502	20.447
6	1.228	0.0776	0	23500	18.022	9.782	16.111
7	1.252	0.1071	0	22700	18.677	12.747	17.804

The data selected for forecast with ANN is shown in the table provided above. The prediction was accurate with the ANN network performing better than the scaled data, which was clearly evident. Performing a real statistical comparison would offer more clarity on the analysis. The rescaled data had an MSE of 34.0523, whereas the ANN predicted outcome achieved a significantly lower MSE of 2.3035, indicating a marked enhancement compared to the rescaled result. In previous instances, the largest percentage differences were found to be 55.87 and 15.13 respectively. Furthermore, almost all results, exactly 78% when employing artificial neural networks for forecasting, are contained within a 10% margin of error. The statistical analysis shows that the accuracy of the ANN prediction is significantly better for the specified condition than the scaled data when compared to the experimental results.

4.3.2.2. Film boiling of Forced Liquid-phase convection

To predict the result of film boiling over vertical surface, low superheat and forced convection condition is also used. An experiment of Jouhara et al. [47] has been taken to apply the ANN network. An experimental study was performed on transient film boiling, using varying coolant velocities, on two spheres of different sizes, two cylindrical specimens of different lengths in parallel flow, a cylinder in cross flow, and two flat plates of different lengths. Using ANN network with input parameters led to remarkable Nusselt number results. The below table compares experimental, scaled, and predicted Nusselt numbers visually for few samples.

Table 4.8: Comparison table for the total Nusselt number of experiment, scale and ANN prediction for low superheat and forced liquid-phase convection for a vertical cylinder							
Sl. No.	Ja_{sup}	Ja_{sub}	Re_l	Gr_v	$Nu_{expt,tot}$	$Nu_{scale,tot}$	$Nu_{ann,tot}$
1	0.196	0.0273	944	236000	31.236	29.486	29.905
2	0.204	0.0273	944	227000	30.4195	27.939	28.566
3	0.218	0.0382	915	216000	32.575	35.665	33.000
4	0.248	0.0273	944	194000	26.287	21.717	25.259
5	0.256	0.0382	915	188000	27.830	28.890	28.264
6	0.295	0.0382	915	164000	24.146	23.836	25.829

The table above displays the data chosen for prediction using ANN. The prediction was correct, as the ANN network outperformed the scaled data, which was clearly visible. Conducting an actual statistical comparison would provide greater insight into the analysis. The MSE for the rescaled data was 7.0581, while the ANN predicted result had a much lower MSE of 1.7980, showing a significant improvement over the rescaled data. In past occasions, the biggest variations were identified as 17.38 and 8.15. Moreover, nearly all findings, specifically more than 92% with the use of artificial neural networks for prediction, fall within the 8% margin of error. Statistical analysis indicates that the accuracy of the ANN prediction is notably superior for the specified condition compared to the scaled data in relation to the experimental outcomes.

ANN prediction results show consistent accuracy in calculating Nusselt number for various film boiling conditions examined over vertical surfaces. Mean Squared Error measures proximity of regression line to data points by averaging squared errors, indicating expected value of error loss. A column bar graph compares MSE of Scale analysis and ANN prediction with experimental results for film boiling over vertical flat plate for visual accuracy evaluation.

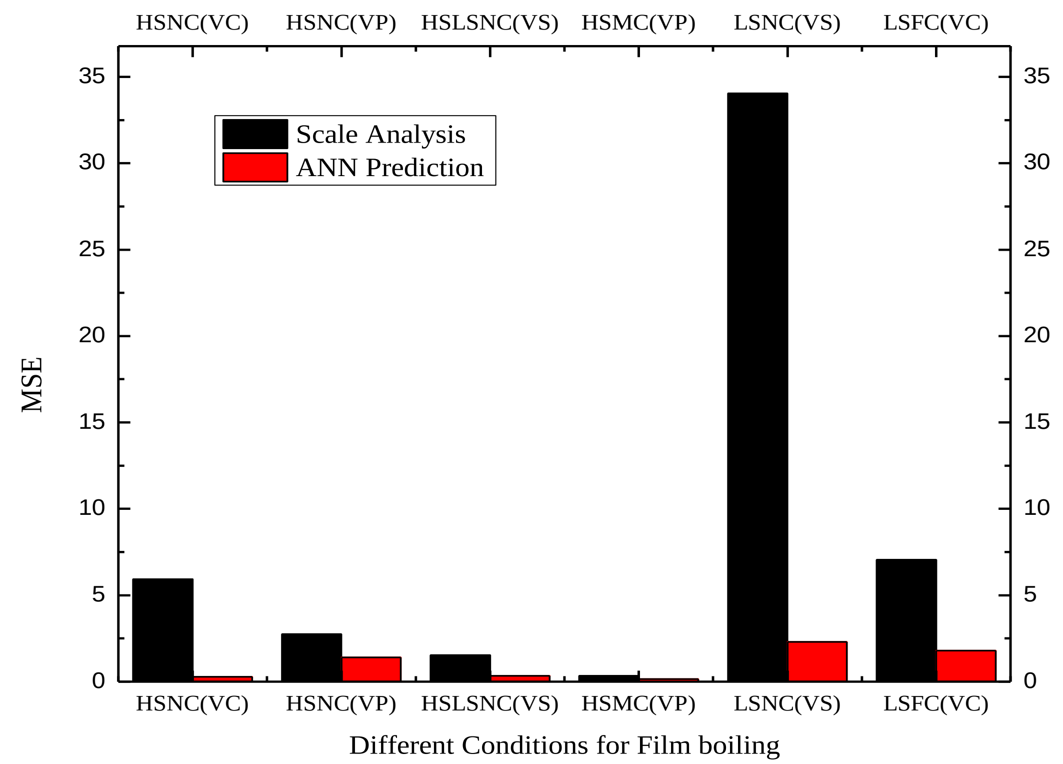


Fig. 4.3: Mean Squared Error bar graph for the results from scale analysis and ANN prediction comparing with the experimental data for film boiling

The optical visualization shows the comparison of accuracy in heat transfer calculation between Scale analysis and ANN prediction for film boiling conditions. The ANN predictions demonstrate superior precision in all conditions, outperforming the scale analysis. Despite different network architectures for high and low wall superheat film boiling, the ANN model consistently delivers better results. The variation in bar heights indicates the reliability of the ANN model.

Chapter 5

Conclusion

The overall thesis work is done in order to predict the heat transfer for different stages of pool boiling, especially Nucleate boiling and Film boiling heat transfer. Calculation of heat transfer in pool boiling is always a challenging problem either by experimentally, analytically or numerically. The problem was well defined and the solution procedure is analysed precisely. The obstacles for both the experimental and scale analysis are mentioned. Thus the aim was to predict the heat transfer by numerical simulation using Artificial Neural Network (ANN).

The results of the prediction are mentioned in the previous chapter. Although all the tested dataset was separated from the trained ones, the network gives spectacular outcomes for every conditions. This implies the accuracy and precision of the ANN network model. The pictorial and the tabular representations report the visual results for the three methods for solving the defined problems.

If the focus is on the statistical errors, then the variation of Mean Squared Errors is the primary parameter to define the better method for heat transfer calculation. The overall analysis evolves as the highest MSE amongst all the predictions is 2.3035, which is statistically fine for a wide range of dataset. The minimum MSE amongst all those operations is 0.0093, which is a remarkable outcome and describes about the closeness of the ANN predicted result to the existing experimental results.

The accuracy and the precision of the ANN network can be described by the error band calculated previously. The overall tested dataset stands in an extraordinary position in case of the range of errors. Overall 93% tested data fall within a 10% margin of error for the ANN model. Thus, the statistical approach states that the ANN is a very suitable computational tool to predict the heat transfer for the problems mentioned earlier.

The ANN is a very fast computational method by which the predictions can be made. For the existing dataset, it can train, validate and test the as per requirements. It also overcomes all the obstacles come in the way to solve heat transfer problem. It overlapped the correctness of scale analysis and stands in a very close position to experimental data. Such a computational model with fast processing and fine order of accuracy would be very helpful in order to solve the problem related to boiling heat transfer. The tool is very useful as it doesn't have the difficulties of processing. The network takes lesser time to forecast the outcome, which is a needy requirement.

Scope of Future work:

The present ANN model utilized a host of multiphase boiling problems of complex nature with better accuracy as compared to existing correlations. Hence, the ANN models can be used for prediction of heat transfer with problems with complexities in geometry and/or physics, where experimental correlations show considerable error. This method can also be utilized as a tool for solving other problems related to heat transfer as well as fluid mechanics, where experimental data are not readily available.

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