

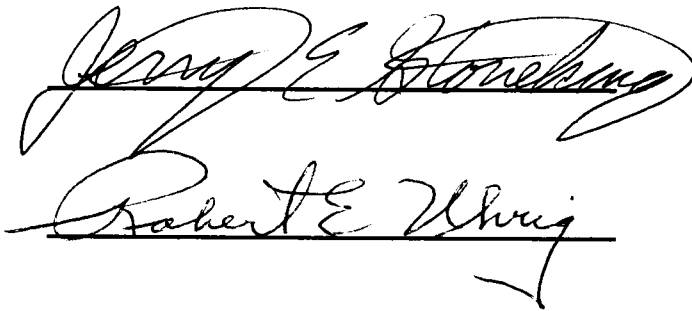
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E. Marcia Katz, Major Professor

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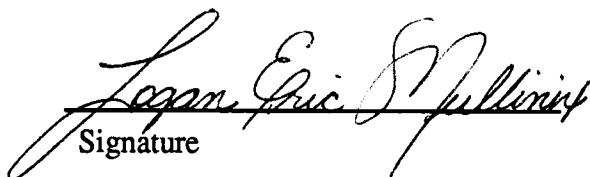
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A New Technique for Estimating the Bulk Fluid Temperature of Stratified Flow in Pressurized Water Reactors

A Thesis

Presented for the Master of Science Degree

The University of Tennessee, Knoxville

Logan Eric Mullinix

December 1992

DEDICATED TO

**My parents, Joline Mullinix and the late Lester Mullinix
and my wife Pamela Rene'**

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ABSTRACT

In some Westinghouse reactors, the computed hot-leg bulk temperature is being biased by thermal stratification of the core exit flow. The stratification results from large temperature differences between the inner and outer regions of the core exit flow and limited fluid mixing between the core exit and the hot-leg temperature sensors. Previously, the bulk temperature obtained from hot-leg temperature measurements was considered to be an accurate estimate, but recent studies suggest that the computed bulk temperature is changing without corresponding flow changes.

The objectives of this research are to develop a method for estimating the hot-leg bulk fluid temperature from exterior pipe surface temperatures and to investigate the relationship between the core exit temperatures and the fluid temperatures measured in the hot-leg(s). The basis for the proposed estimating method is that as the flow mixes along the pipe, the surface temperature of the pipe will approach the bulk fluid temperature within some small temperature difference. The process of determining the bulk fluid temperature begins with discrete measurements of the pipe surface temperature. These measurements are processed into axial temperature profile(s) that is extrapolated to their asymptotic value(s). The bulk temperature is computed by averaging the final asymptotic temperature(s) and adjusting this value for the temperature drop across the pipe wall.

An experimental facility was constructed to simulate stratified flow and verify the process of estimating the bulk fluid temperature from pipe surface temperatures. The facility was used to perform experiments with various degrees of flow stratification. The experimental results are bulk temperature estimates that on an average are within 0.15°F (0.13%) of the actual bulk temperature.

One of the primary agents believed to promote stratification in the reactor coolant system, RCS, is the temperature variations present in the core exit flow. Therefore, the influence of the core exit temperature on the bulk fluid temperature is analyzed. The analysis uses artificial neural systems technology to develop this relationship using core exit temperature measurements and RSC hot-leg temperature measurements made during reactor operations. The results of the analysis are promising but are restricted by the availability of measured data; only one set of data was available. Therefore, the results are not conclusive, but they illustrate the potential benefits of this procedure if more information becomes available.

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LIST OF SYMBOLS AND ABBREVIATIONS

Symbol	Description	Units
A_c	Cross Section Area	ft^2
c_v	Specific heat at constant volume	$\text{BTU/lbm-}^\circ\text{F}$
E'_{in}	Energy entering a control volume	BTU/s
E'_g	Energy generated in a control volume...	BTU/s
E'_{out}	Energy leaving a control volume	BTU/s
E'_{st}	Energy Stored in a control volume	BTU/s
E'_t	Total energy transported by a fluid	BTU/s
$^\circ\text{F}$	Degrees Fahrenheit	
h	Convective coefficient	$\text{BTU/hr ft}^2 \text{ }^\circ\text{F}$
i	Unit vector in the x direction	
j	Unit vector in the y direction	
k	Thermal conductivity	$\text{BTU/hr-ft }^\circ\text{F}$
m'	Mass flow rate	lbm/s
n	Unit vector normal to surface	
PE	Processing element	
PWR	Pressurized water reactor	
q	Heat transfer rate	BTU/hr
Q	Volmetric Flow Rate	ft^3/s
RCS	Reactor Coolant System	
RTD	Resistance thermal detector	
r	Radial pipe dimension	ft
T	Temperature	$^\circ\text{F}$
T_b	Bulk fluid temperature	$^\circ\text{F}$
TC	Thermocouple	
T_{eb}	Estimate of bulk temperature	$^\circ\text{F}$
T_{mb}	Measured bulk temperature	$^\circ\text{F}$
u	Fluid velocity	ft/s
u_b	Bulk fluid velocity	ft/s

∇	Gradient operator	
Ω	Omega, denotes solution space	$\mathcal{H} \times \mathcal{H}$
$\partial \Omega_1$	Boundary of Ω	
$\mathcal{H}^2$	Two dimensional Euclidean space	$\mathcal{H} \times \mathcal{H}$
ρ	Fluid density	slugs/ft ³

Chapter 1

INTRODUCTION TO STRATIFIED FLOW AND BULK FLUID TEMPERATURE

Introduction

In nuclear power generating facilities, the control, protection, and plant-wide monitoring systems rely on the precise measurement of process variables. One of the primary measured variables is fluid temperature. A recent problem experienced in some pressurized water reactors (PWRs) indicates that the bulk fluid temperature computed for the reactor coolant system, RCS, is biased by thermal stratification [1]. To overcome this problem, a newly proposed method estimates the bulk fluid temperature from measurements of the external pipe surface temperature. This method relies on the theory that, as a fluid mixes inside the pipe, the temperature of the fluid approaches an equilibrium that can be estimated using measurements of the pipe surface temperature.

One of the primary uses of the RCS bulk fluid temperature is in thermal energy calculations, which is typically sensitive to the accuracy of the bulk temperature. Stratification in the RCS piping of some PWRs affects the accuracy of the bulk fluid temperature estimates. Reports indicate that errors in the computed bulk fluid temperature result in decreases of the computed flow rate of the RCS [2]. Although other measurements show that the flow rate does not change, better estimates of bulk fluid temperature are needed to show that the RCS is operating within design limits.

Currently, three resistance temperature detectors, RTDs, measure the fluid temperature in each hot-leg flow of the RCS. The sensors are in thermowells that are mounted in ported fixtures and extend into the flow as shown in Figure 1.1. Figure 1.2 shows the equal spacing of the hot-leg RTDs around the circumference of the pipe (relative to a sensor on top of the pipe). Typically, the fluid temperature measured by each sensor differs, and the average of these measurements are used as an estimate of the bulk temperature. Recent data from some PWRs indicates that the RTD measurements vary as

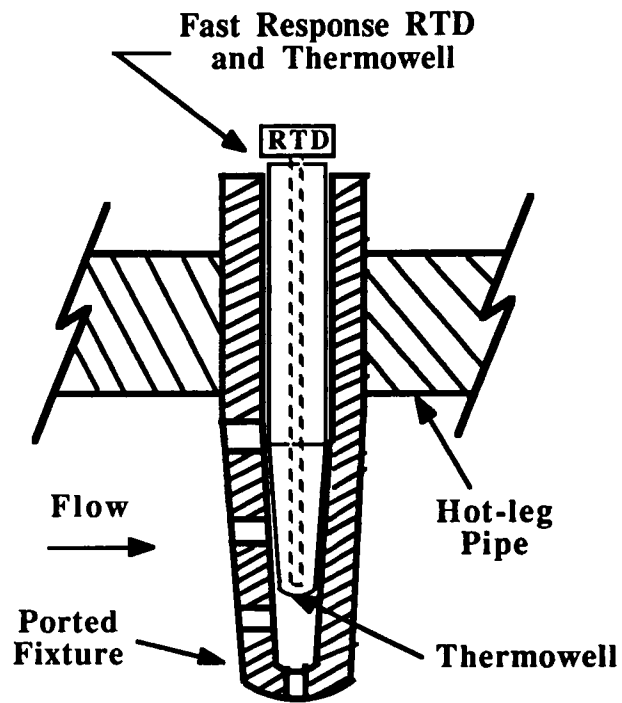


Figure 1.1 Hot-leg RTD Mounting Detail

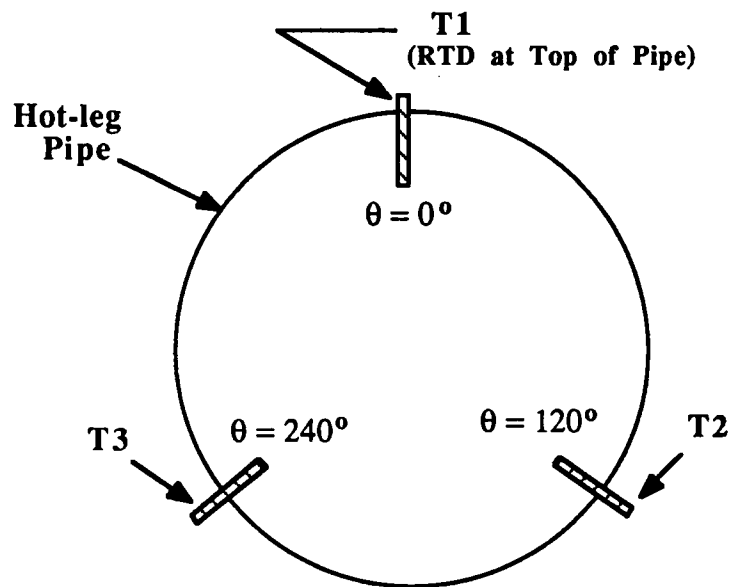


Figure 1.2 RTD Mounting Locations in Hot-leg of RCS

much as 10 °F [1][2] and therefore bias the computed bulk fluid temperature.

Problems Estimating Bulk Fluid Temperature of Stratified Flow

Bulk fluid temperature is used to define the rate at which energy is being transported by a fluid. For a fluid with a constant temperature, the bulk temperature is equal to the fluid temperature. In the absence of a constant fluid temperature, the bulk temperature, which characterizes the bulk energy being transported, must be computed. An interpretation of the bulk fluid temperature is an equilibrium temperature that is commonly referred to as the mixing cup temperature [3] [4]. A physical interpretation of the mixing cup temperature is the temperature of a cross section of fluid removed from a flow and mixed adiabatically until reaching thermal equilibrium.

Why are bulk temperatures needed? The bulk fluid temperature defines the mean temperature of a fluid in the absence of a fixed free stream temperature. They are typically used in thermal energy balances and transport equations. Obtaining the theoretical bulk temperature of a fluid flowing in a pipe requires knowledge of flow characteristics such as the temperature and velocity gradients. This information frequently is not available in practical situations. Rather, estimates of the bulk fluid temperature are obtained from measurements.

Common techniques of fluid temperature measurement use variations of the direct measurement method [5]. One variation places temperature sensing elements in the main channel of fluid flow. If more than one sensor is used, the bulk temperature estimate of a uniform flow is the average measured temperature. A second variation removes samples of the fluid from the flow and allows the fluid to mix before the temperature is measured. Computing the bulk temperature of the RCS typically uses one of these methods.

As the complexity of the fluid temperature distribution increases, estimates using these methods may become less accurate. Abrupt changes in the radial fluid temperature distribution characterize one complexity. These abrupt changes in fluid temperature are often referred to as temperature stratification. Temperature stratification is a phenomenon in which the temperature of a given mass of fluid is different from the adjacent fluid. If the temperature differences become large, discrete measurements may not represent the bulk temperature of the fluid.

Temperature stratification can result in fluid processes that are characterized by non-uniform fluid temperatures and limited mixing. The degree of stratification can greatly affect the ability to accurately and economically estimate the bulk fluid temperature. For highly stratified flow, accurate estimates may be difficult to obtain.

Estimating the Bulk Fluid Temperature From Pipe Surface Temperatures

The process of determining the bulk fluid temperature involves approximating the equilibrium temperature of a fluid using discrete pipe surface temperature measurements. The estimating process is evaluated experimentally using an experimental facility that was constructed to simulate stratified flow in a horizontal pipe. Thermocouples (TC's) are used to monitor the pipe surface temperature and measure the actual bulk fluid temperature (see Figure 1.3). The measured surface temperatures are processed into estimates of the bulk temperature that can be compared to the measured bulk fluid temperature.

The apparatus induces various degrees of stratification. The injection of two feed water sources into the pipe that have different temperatures produces the primary source of stratification. Modifications also produce various degrees of stratification by introducing flow obstructions and varying the inlet feed water temperatures and flow rates.

Organization

This thesis presents the concepts, development, and conclusions of a new method to estimate the bulk temperature of a fluid flowing in a pipe using pipe surface temperature measurements. Also presented is an analysis that shows the influence of core exit temperatures on the measured temperature in the hot-legs of the RCS.

Chapter 2 introduces the theoretical description of bulk fluid temperature and fluid stratification. Also presented are several processes by which surface temperatures can be used to estimate of the bulk fluid temperature. Chapter 3 discusses the experimental procedures used to study stratified flow in a horizontal pipe. Chapter 4 examines the experimental and computational results. Chapter 5 presents the foundation for another technique that may further the estimating process. Chapter 6 investigates the background, theory, and results of an analysis that investigates the relationship between the core exit fluid temperatures and the hot-leg temperatures. Chapter 7 summarizes the results and presents the research conclusions.

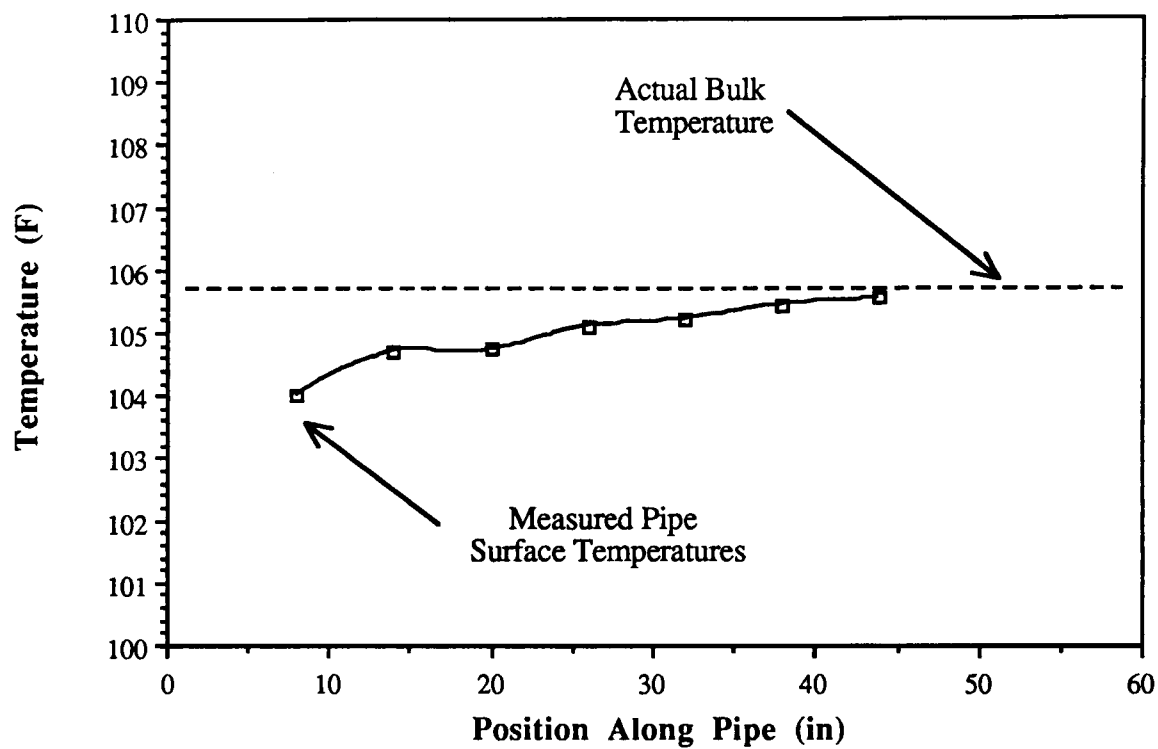


Figure 1.3 Pipe Surface Temperature Profile of Stratified Flow

Chapter 2

THEORETICAL AND EXPERIMENTAL ASPECTS OF ESTIMATING BULK FLUID TEMPERATURE

Introduction

This chapter presents the theoretical aspects of estimating the bulk fluid temperature and the problems associated with using direct fluid measurements. For some conditions such as stratified flow, direct fluid measurements may result in biased estimates. Therefore, an experimental method is presented for estimating the bulk temperature. The process of estimating the bulk fluid temperature is divided into three phases. In the first phase, discrete measurements of the pipe surface temperature are processed to produce axial temperature profiles. Three techniques are examined for generating these profiles. In the second phase, the profiles are extrapolated to their asymptotic value (see Figure 1.3) which represents an approximation of the equilibrium pipe surface temperature. In the final phase, the asymptotic values are averaged and compensated for the temperature drop across the pipe wall.

Theoretical Bulk Temperature and Stratified Flow

Before presenting the new method, the theoretical aspects of computing the bulk temperature and its relationship to stratified flow are considered. The presentation begins with the law of Conservation of energy, which all modes of heat transfer must satisfy. Figure 2.1 depicts a control volume and the possible modes for transferring energy to and from the control volume. For the control volume, the conservation rate equation shown in equation 2.1 states that

$$E'_{in} + E'_g - E'_{out} = E'_{st} \quad (2.1)$$

where E'_{in} is the energy entering the control volume,

E'_g is the generated energy,
 E'_{out} is the energy exiting the control volume, and
 E'_{st} is the stored energy.

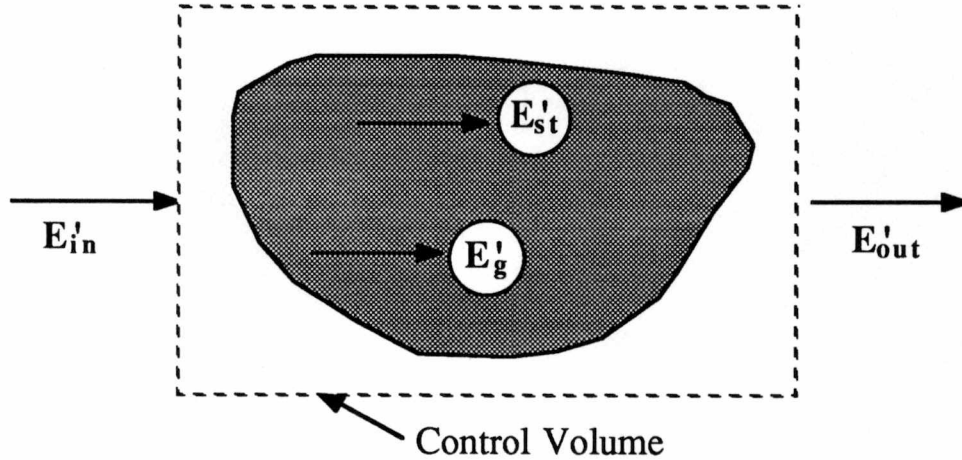


Figure 2.1 Conservation of Energy for a Control Volume

In the absence of fixed free stream properties such as temperature and velocity, it is necessary to define a set of bulk properties to evaluate the conservation rate equation [4]. The definition of the bulk temperature of a cross section of fluid is derived from the definition of the energy transport rate. The energy transport rate, E'_t , may be defined by integrating the product of the mass flux ($\rho u(r)$) and the internal energy per unit mass ($c_v T$) over the cross section. The rate equation is

$$E'_t = \int_{A_c} \rho u(r) c_v T(r) dA_c \quad (2.2)$$

where A_c is the cross sectional area,
 ρ is the fluid density,
 $u(r)$ is the radial velocity distribution,
 c_v is the specific heat, and
 $T(r)$ is the fluid temperature at radius r .
 If the bulk temperature is defined such that

$$E'_t = m' c_v T_b \quad (2.3)$$

where m' is the mass flow rate and

T_b is the bulk fluid temperature,

it follows that

$$T_b = \frac{\int_{A_c} \rho u(r) c_v T(r) dA_c}{m' c_v}. \quad (2.4)$$

If the flow is incompressible,

$$m' = \rho u_b A_c \quad (2.5)$$

where c_v is constant and

u_b is the bulk fluid velocity.

The expression for the bulk temperature becomes

$$T_b = \frac{2}{u_b r_o^2} \int_0^{r_o} u(r) T(r) r dr \quad (2.6)$$

where r_o is the inside radius of the pipe.

Finally, if the velocity distribution is assumed to be constant, equation 2.6 reduces to

$$T_b = \frac{2}{r_o^2} \int_0^{r_o} T(r) r dr. \quad (2.7)$$

From equation 2.7, the bulk temperature of the fluid corresponds to the mean value of the temperature distribution. Typically, the temperature distribution, $T(r)$, and the velocity distribution, $u(r)$, which defines the bulk temperature are not analytically defined. However, if the flow can be assumed to have a constant velocity distribution, the bulk temperature can be approximated by averaging discrete fluid temperature measurements. The assumption of a constant fluid velocity is reasonable for flow with a Reynolds number $> 300,000$ [6]. The Reynolds number for the RCS flow is greater than 300,000 (see Appendix E for calculations of Reynolds number). Therefore, averaging the discrete temperature measurements should produce a statistical estimate of the bulk temperature. This process is used in some reactor coolant systems.

The problems associated with discrete temperature measurement arise when the measured temperatures do not represent the actual temperature of the fluid. Figure 2.2 depicts a non uniform (stratified) fluid flowing in a pipe fitted with two temperature sensors; the illustration suggests that the bulk or mixing cup temperature computed from the sensors will be biased to a higher temperature. However, conduction and mixing will reduce fluid stratification as the flow progresses axially [3][4][7]. For piping systems where heat loss is negligible, the conservation of energy and process of diffusion require that the temperature of the fluid approach an equilibrium. As the fluid temperature approaches equilibrium, the surface temperature of the pipe approaches equilibrium.

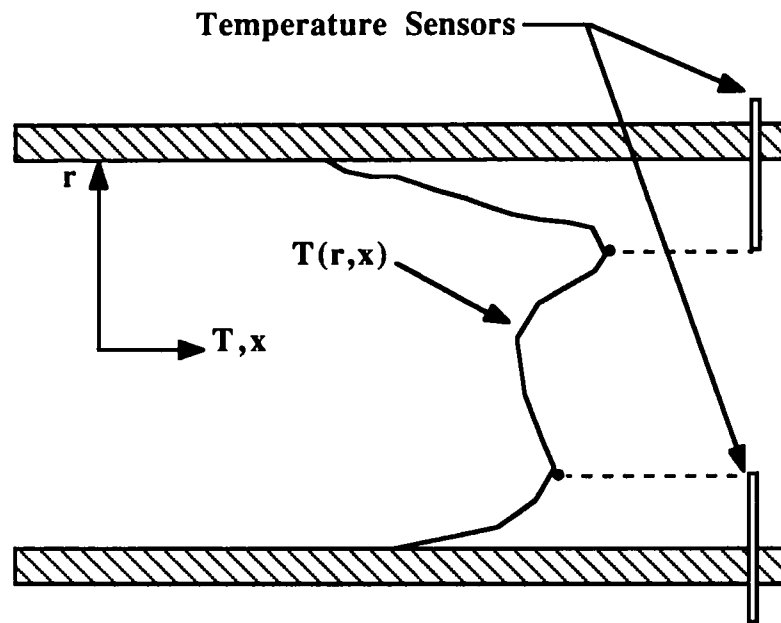


Figure 2.2 Discrete Temperature Measurement of Stratified Fluid Flow

Estimating Bulk Fluid Temperature From Pipe Surface Temperature Measurements

If the length of the pipe is sufficient, a stratified fluid will mix. For this case, the temperature of the fluid can be measured directly. For flows that are not well mixed, a new method is proposed. The practical application of this method is evaluated experimentally using experiments designed to study some of the conditions found in the RCS, such as stratification and fluid swirl. The experiments are conducted using an experimental facility in which the basic component is a horizontal insulated pipe. The facility is capable of producing various degrees of stratified flow and fluid mixing.

Developing the Piping of the Experimental Apparatus

Effect of Surface Convection. For non-adiabatic conditions, convection reduces the amount of energy being transported by the fluid. The effect of convection can be profound if the pipe is not well insulated. To investigate the effect of convection on the axial change in bulk temperature, consider fluid flowing in the pipe shown in Figure 2.3 [4]. The result of applying an energy balance to the differential control volume and integrating over the length of the pipe is

$$\frac{\Delta T_b}{\Delta x} = \frac{q_{conv}}{m' c_v} \quad (2.8)$$

where q_{conv} is the total heat transfer rate, and x is the axial length of the pipe. Equation 2.8 shows that the axial temperature change of the fluid can be significant for values of the mass flow rates that are small compared to the value of the total convective heat transfer rate. For example, given a constant convective heat rate and flow properties, increasing the mass flow rate decreases the axial change in the bulk temperature,

When equation 2.8 is applied to the piping of the RCS and experimental apparatus(see Chapter 3 for detailed description of experimental apparatus), the axial change in the bulk temperature is small (see Appendix E). Therefore, the change in the bulk temperature over the length of the pipe is considered negligible for both systems.

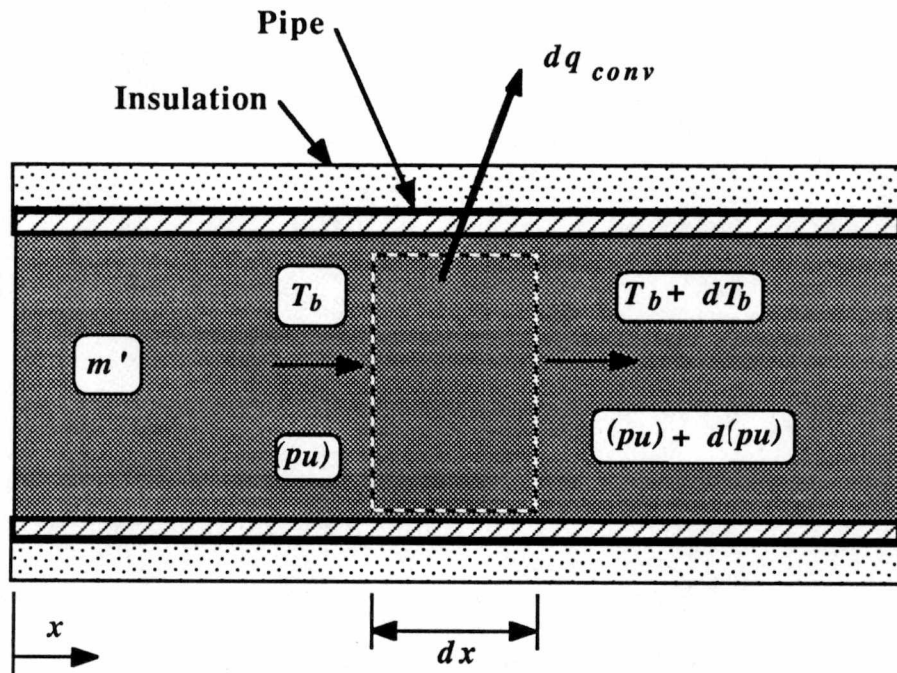


Figure 2.3 Differential Control Volume for Flow in a Pipe

Circumferential Temperature Variations Between the Fluid and the Exterior Pipe Surface. The difference between the fluid temperature and the pipe surface temperature depends upon the thermal properties of the piping system and the boundary conditions imposed by the environment. If the temperature distribution at a cross section remains constant, this relationship may be analyzed with the diffusion equation (equation 2.9). For fluid flow in a horizontal insulated pipe with exterior surface convection, the boundary conditions necessary to solve equation 2.9 are given by equations 2.10 and 2.11.

$$L(T) = -\nabla \cdot k \nabla T = 0 \quad \text{on } \Omega \in \mathcal{R}^2 \quad (2.9)$$

$$l(T) = k \nabla T \cdot \mathbf{n} + h_f(T - T_f) = 0 \quad \text{on } \partial\Omega_1 \quad (2.10)$$

$$l(T) = k \nabla T \cdot \mathbf{n} + h_a(T - T_a) = 0 \quad \text{on } \partial\Omega_2 \quad (2.11)$$

where ∇ is the gradient operator ($i\partial/\partial x + j\partial/\partial y$), k = thermal conductivity, and Ω defines a region in two dimensional Euclidean space ($\mathcal{R}^2$). For a positive diffusion coefficient, $k = k(x,y) > 0$, equation 2.9 defines an elliptic equation. Therefore, the linear combination of the boundary conditions ($\partial\Omega_1 \cup \partial\Omega_2$) must define the total boundary ($\partial\Omega$). By convention, the outward directed unit normal vector from Ω is denoted $\mathbf{n}$, and i and j are the unit vectors parallel to the x and y axes, respectively. Finally, h_f and h_a are the convective coefficients of the internal fluid and the exterior air, respectively, and T_f and T_a are the temperatures of the internal and external fluids, respectively.

For flow conditions where the fluid temperature, T_f , varies circumferentially, the temperature difference between the fluid and the exterior surface will also vary. The magnitude of the variation depends upon the thermal properties of the piping system and the boundary conditions. These variations are present in the RCS and experimental apparatus piping. Figures 2.4 and 2.5 show theoretical temperature variations between the fluid and exterior pipe surface for properties typical of the RCS and the experimental apparatus, respectively. These figures illustrate a problem that may arise from using surface temperature measurements: how should the surface temperatures be processed to compensate for the temperature drop across the pipe wall in the bulk temperature estimating process? This question is addressed in the following sections that describe the estimating process.

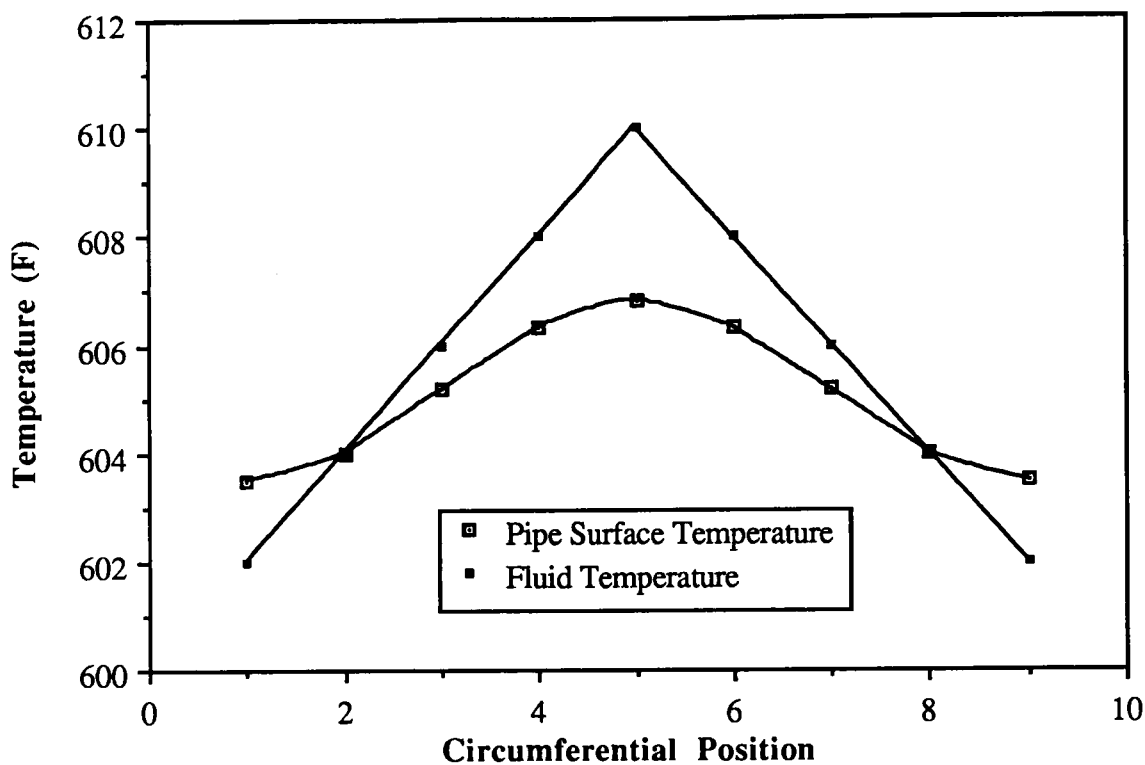


Figure 2.4 Temperature Variations Between the Fluid Temperature and the Exterior Surface Temperature for a Hot-leg Pipe.

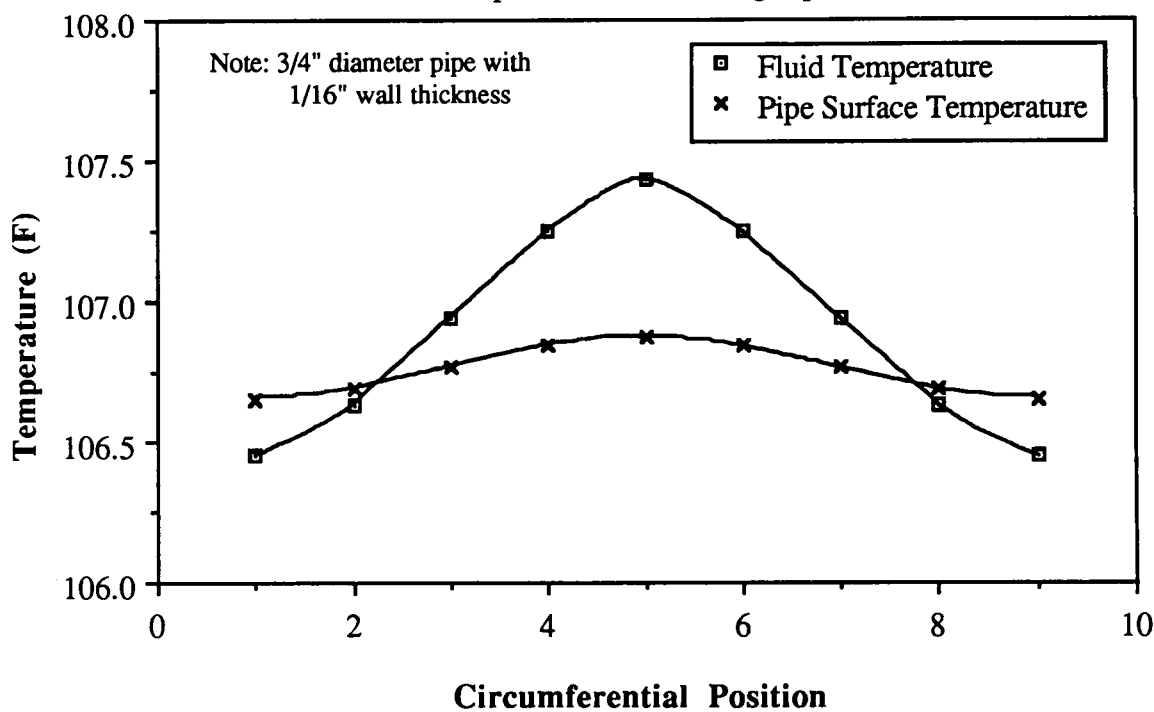


Figure 2.5 Temperature Variations Between the Fluid Temperature and the Exterior Surface Temperature for Experimental Apparatus Piping.

Experimental Apparatus

The experimental apparatus consists primarily of an insulated pipe that transports a stratified fluid. Twenty-eight temperature sensors are mounted to the pipe surface (the number of sensors is limited by the available processing equipment). The location of the temperature sensors is shown in Figure 2.6. There are four sensors mounted around the circumference of the pipe at each of seven axial positions. The sensors at each axial position form a *sensor ring*. The four sensors in each ring are equally spaced around the pipe with one sensor located on top of the pipe ($\theta = 0$). For future reference, the location of the sensors will be referred to by their angular position (i.e. $\theta = 0, 90, 180$, and 270).

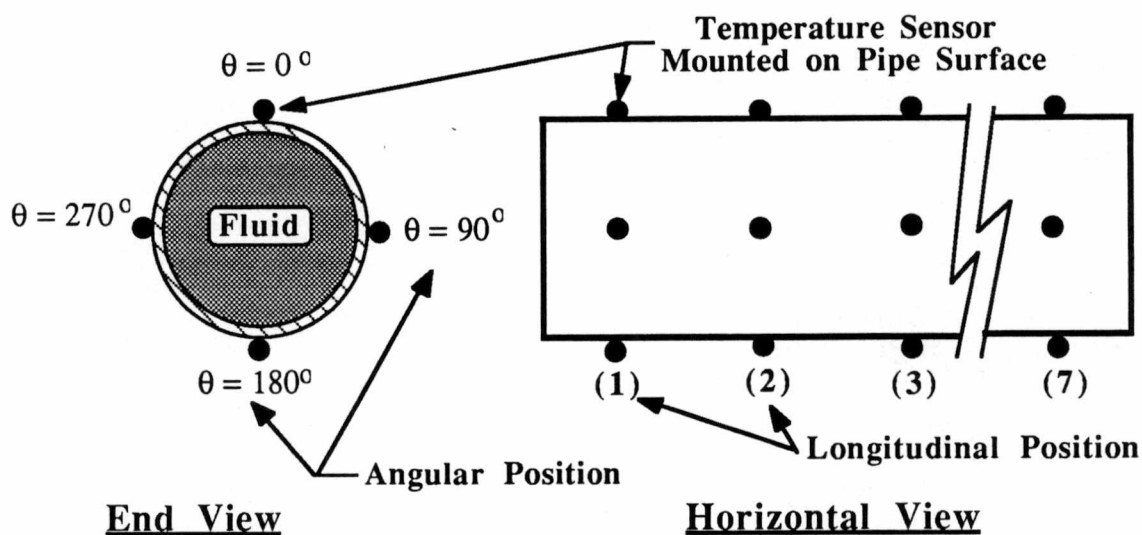


Figure 2.6 Temperature Sensors Mounted on Pipe Surface of Experimental Apparatus

Three Phases of Estimating the Bulk Temperature

Phase I: Generating Axial Profiles

The first phase of estimating the bulk temperature begins by arranging the surface temperature measurements into axial profiles. Three techniques of generating the profile are examined. The first profile method is based on the circumferential position of the temperature sensor and will be referred to as the *Position Profile Method*. Using this method, four axial profiles are generated that correspond to $\theta = 0$, $\theta = 90$, $\theta = 180$, and $\theta = 270$, respectively. The second method generates profiles by ranking the temperatures according to magnitude at each axial position. The outcome is profiles that track the axial temperature variations according to rank at each position. Ranking the temperature measurements at each axial position is an attempt to monitor the axial change in the fluid

temperature of a swirling fluid. This technique will be referred to as the *Ordered Profile Method*. The third technique generates a single profile, and it is based on the average temperature at each axial position (sensor ring). This technique will be referred to as the *Average Profile Method*.

Phase II: Computing an Equilibrium Surface Temperature

Once the axial profiles are developed, the estimation process continues by computing an exponential least squares fit of each profile. These functional approximations represent the axial change in the pipe surface temperature as fluid mixes and stratification reduces. For flows that do not reach equilibrium, the equilibrium temperature of the pipe surface can be approximated by computing the asymptotic value of each profile.

Exponential functions are commonly found in the analytical solution to transient problems such as free-damped vibrations and diffusion [8][9][10] and are useful when approximating experimental data that has exponential behavior. Although the exponential functions are nonlinear, they can be linearized. Once linearized, curve fitting methods such as least squares can be applied to determine the functional approximations of the experimental data.

The derivation of the least square method is not presented, rather an overview and its application to exponential functions are discussed. Given experimental data, defining an analytical function that follows the general shape of the data introduces residuals, defined as the difference or error between the measured value and the value of the function. The least squares method minimizes the square of the residual error. Consider the exponential function of the form

$$y = a e^{b/x} \quad (2.12)$$

where a and b are constants, and x corresponds to the length of the pipe. The linear form of this equation is

$$\ln y = \ln a + b/x. \quad (2.13)$$

By letting $z = \ln y$, $c_1 = \ln a$, and $c_2 = b$, equation. 2.13 becomes

$$z = c_1 + c_2/x. \quad (2.14)$$

If the least squares method is applied to exponential data in the form of equation 2.14, the effect would be to minimize the logarithmic residual, R_i , instead of the actual residual, r_i , [9]. Figures 2.7 and 2.8 illustrate the residuals R_i and r_i , respectively.

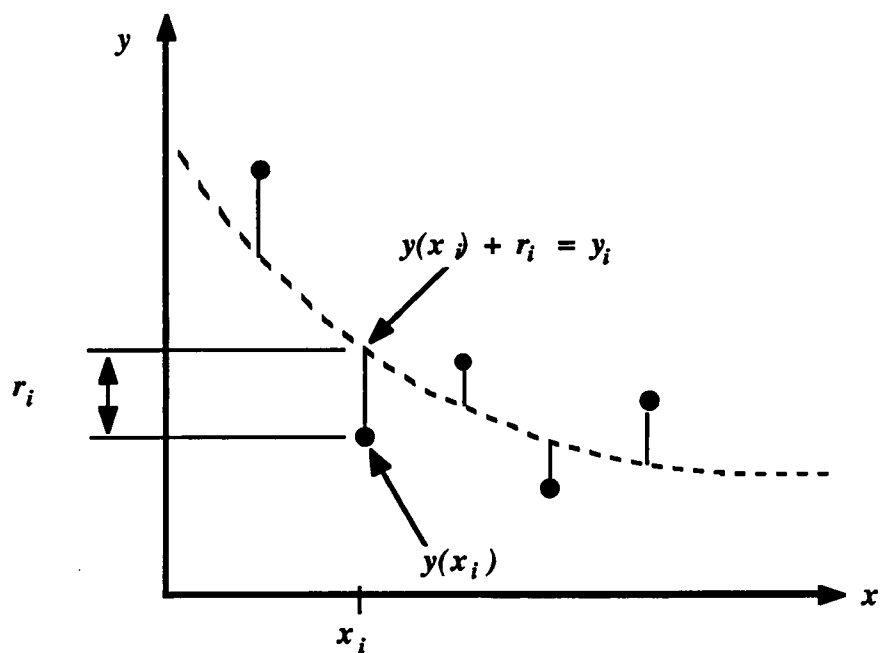


Figure 2.7 Residuals, r_i , of the $a e^{b/x}$ Approximation

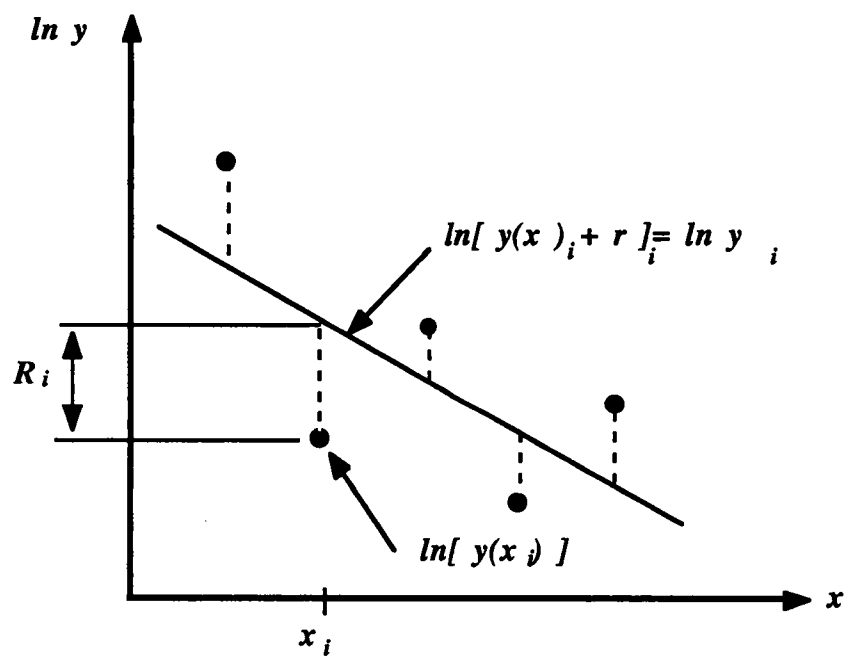


Figure 2.8 Residuals, R_i , of the $\ln(y)$ Approximation

Solving equation 2.14 for the logarithmic residual, R_i , yields

$$R_i = c_1 + c_2/x_i - \ln y_i \quad (2.15)$$

where the residual of the approximation, $a e^{b/x}$, is

$$r_i = a e^{b/x_i} - y_i. \quad (2.16)$$

Expressing the error, R_i , in terms of r_i and $\ln y$ yields

$$R_i = \ln(y(x_i) + r_i) - \ln(y(x_i)) \quad (2.17a)$$

or

$$R_i = \ln(1 + r_i/y(x_i)). \quad (2.17b)$$

Using the definition of a logarithm, equation 2.17b may be restated as

$$e^{R_i} = 1 + r_i/y(x_i) \quad (2.18)$$

where the series expansion of e^{R_i} is

$$e^{R_i} = 1 + R_i + R_i^2/2! + R_i^3/3! + \dots \quad (2.19)$$

If R_i is assumed to be small, equation 2.19 becomes

$$e^{R_i} \cong 1 + R_i. \quad (2.20)$$

It follows from equations 2.18 and 2.19 that

$$1 + R_i = 1 + r_i/y(x_i). \quad (2.21)$$

Solving for R_i yields

$$R_i = r_i/y_i(x). \quad (2.22)$$

Giving equal weight to the errors in y_i requires minimizing $\sum_i y_i^2 R_i^2$. This is achieved by taking the partial derivative of $\sum_i y_i^2 R_i^2$ with respect to the constants c_1 and c_2 of equation 2.14.

$$\sum_i y_i^2 R_i \frac{\partial R_i}{\partial c_1} = 0 \quad (2.23)$$

and

$$\sum_i y_i^2 R_i \frac{\partial R_i}{\partial c_2} = 0. \quad (2.24)$$

Solving equations 2.23 and 2.24 simultaneously for the constants c_1 and c_2 completes the least squares approximation of the experimental data. After computing the exponential expression, the asymptotic value of each profile is found by taking the limit as x (length of pipe) approaches infinity.

$$y(x \rightarrow \infty) = a e^{b/\infty} = a \quad (2.25)$$

where a is the asymptotic value of the exponential approximation. Therefore, by applying the exponential least squares procedure to each profile, the asymptotic value(s) can be computed from equation 2.25.

Phase III: Computing the Bulk Temperature

The final phase adjusts the average asymptotic value for the temperature drop between the outer pipe surface temperature and the fluid temperature. The asymptotic value of each profile is not expected to be identical. Measurement uncertainty, computational errors, and the error associated with circumferential temperature variations across the pipe wall will cause differences in the computed asymptotic values. Therefore, the final values are averaged [11]. The bulk temperature is computed from the equilibrium surface temperature by accounting for the temperature drop across the pipe wall.

The measurement uncertainty and computational errors should be considered consistent for all of the experiments. However, the error due to the circumferential temperature variations between the fluid and the adjacent pipe surface is different for each fluid temperature distribution. To understand this error, examine the function of the profile methods. They are designed to track the temperature changes in the fluid as the flow progresses along the pipe. For example, the *Order Profile Method* has the ability to track axial temperature variations of a swirling flow. However, considering the effect of the

circumferential temperature variations, a high temperature portion of the flow may not produce an adjacent high surface temperature. This is illustrated in Figure 2.9 where the highest fluid temperature (position #4) does not correspond to the highest radial surface temperature (position #9).

The error due to the circumferential temperature variations decreases because the flow mixes and stratification decreases. The decreasing nature of the error is included in data used in the extrapolating process. Therefore, the extrapolation process also approximates the asymptotic effect of the error. Ideally, the extrapolating process removes the effect of this error. Since the estimating process involves discrete data and approximations, extrapolating only reduces the error. This is the philosophy used to evaluate the experimental data presented in chapter 4. In the final phase of the estimation process, the asymptotic values are averaged, and the temperature drop across the pipe wall is subtracted. For the experimental apparatus, the temperature drop is determined experimentally and theoretically. For the RCS, the temperature drop can be determined from measurements made during hot-functional operation or from a computational approach such as Finite Element Analysis, FEA.

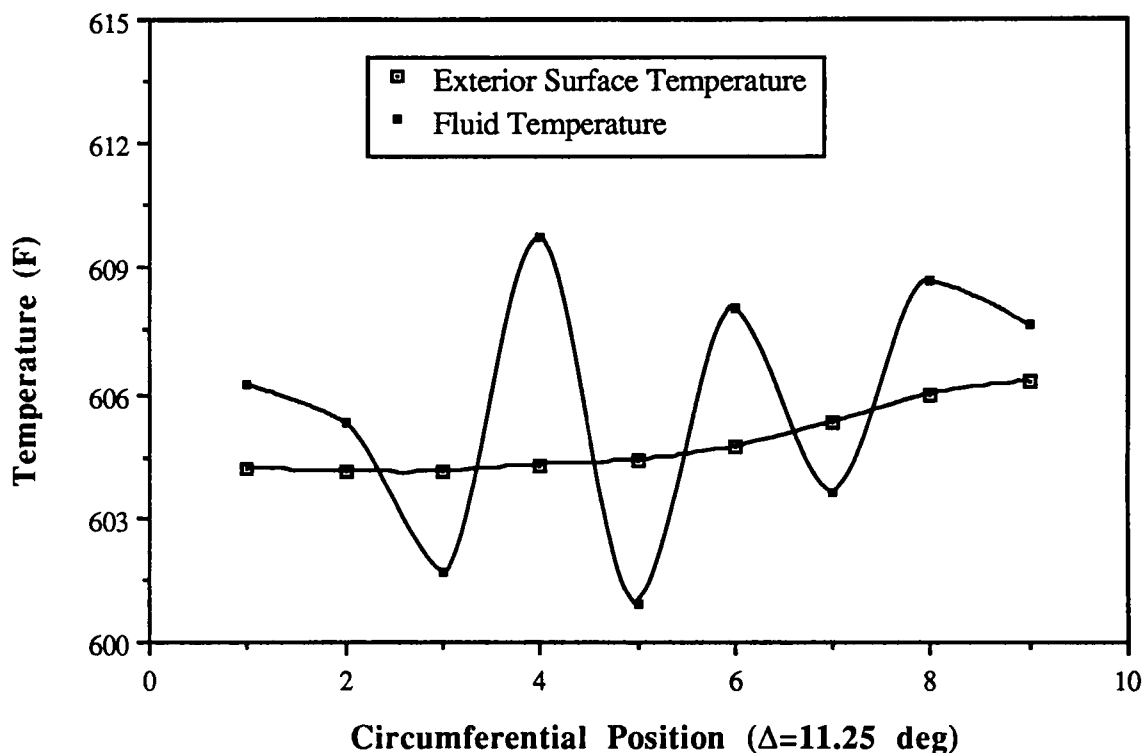


Figure 2.9 Circumferential Temperature Variations Between Fluid and Exterior Pipe Surface

An alternate approach may be to determine the fluid temperature at each axial position of the flow from the measured surface temperatures. This approach may reduce the error associated with the circumferential temperature variations and should be considered for future research. The basis for this approach is the application of a neural network that uses measured surface temperatures to compute estimates of the adjacent fluid temperature. The foundation of this approach is developed in chapter 5.

Chapter 3

EXPERIMENTAL METHODS AND PROCEDURES

Introduction

This chapter presents a description of the experimental facility and procedures. The description defines the function of each component of the apparatus and the relevance of various initial flow conditions. Modifications made to the apparatus and procedures enable the study of various degrees of flow stratification. These modifications include various flow dividers, piping modifications, and feed water temperature and flow rate variations.

Description of Experimental Facility

The experimental facility is shown in Figure 3.1. It consists of a 'Y' pipe fitting that serves as the inlet connection for the hot and cold feed water. The 'Y' fitting is modified with a flow divider. The divider separates the two feed water streams until they enter the horizontal section of pipe. The various divider geometries induce stratification. The design and the expected effect of each divider are discussed in subsequent sections. After passing the divider, the flow is uninterrupted through the horizontal pipe into a collecting tank where the bulk fluid temperature is measured directly.

As the fluid travels through the system, thermocouples, TCs, welded to the pipe monitor the axial temperature variations of the pipe surface. The thermocouples are mounted circumferentially in groups of four at seven cross sections along the length of the pipe. Each group of thermocouples forms a *sensor ring*. At each sensor ring position (cross section), four thermocouples are equally spaced around the circumference of the pipe (see Figure 2.6, p14) with one sensor located on the top of the pipe that corresponds to $\theta = 0$ degrees. The ring occupying position #1 is located eight inches from the entrance of the pipe. The remaining rings are located at six inch intervals along the pipe for a total of seven sensor rings.

The sensor in the collecting tank and those welded to the pipe surface are connected to a 2150 multi-point switching unit. The switching unit consists of manual switches that designate which sensor signal is processed by the 2100A Digital Thermometer. The hot and cold feed water temperatures are measured by thermocouples mounted to the 'Y' and extend directly into the fluid flow. The piping system and the temperature sensors are insulated from the environment with 1/2" foam rubber insulation. One inch of generic foam insulation insulates the collecting tank. A complete equipment list is given in Appendix B.

Experimental Testing Procedure

Testing begins by verifying that all sensors are functioning properly by introducing constant temperature water and observing the temperature variations indicated by each sensor. Next, hot and cold water is introduced to the system. The flow rate is not precisely measured, but approximations are established based on the position of the hot and cold water flow control valves. The flow rates vary between 1 and 4 gallons per minute.

With the flow from the hot water source set, adjustment of the temperature and the flow rate of the cold water determines the temperature difference between the hot and cold feed water. The temperature of the hot water source is held constant, and the cold water temperature is adjusted until the desired temperature difference is achieved. After the temperature and flow parameters are established, the system is monitored until the fluid temperature in the reservoir reaches equilibrium and remains constant for 3 minutes. The total process takes 5 to 10 minutes. Once equilibrium is reached, the temperature of each sensor is recorded sequentially. The bulk and feed water temperatures are closely monitored to identify transients caused by unwanted temperature changes.

Experimental Apparatus Variations

Each experiment is characterized by the type of flow divider, flow feed water rates, and feed water temperatures. By omitting the flow divider, the flow will begin mixing before entering the pipe, and the effect of stratification is reduced. Therefore, to ensure a stratified flow, a flow divider is mounted inside the 'Y' fitting. *Straight, angled, and helical* flow dividers are used.

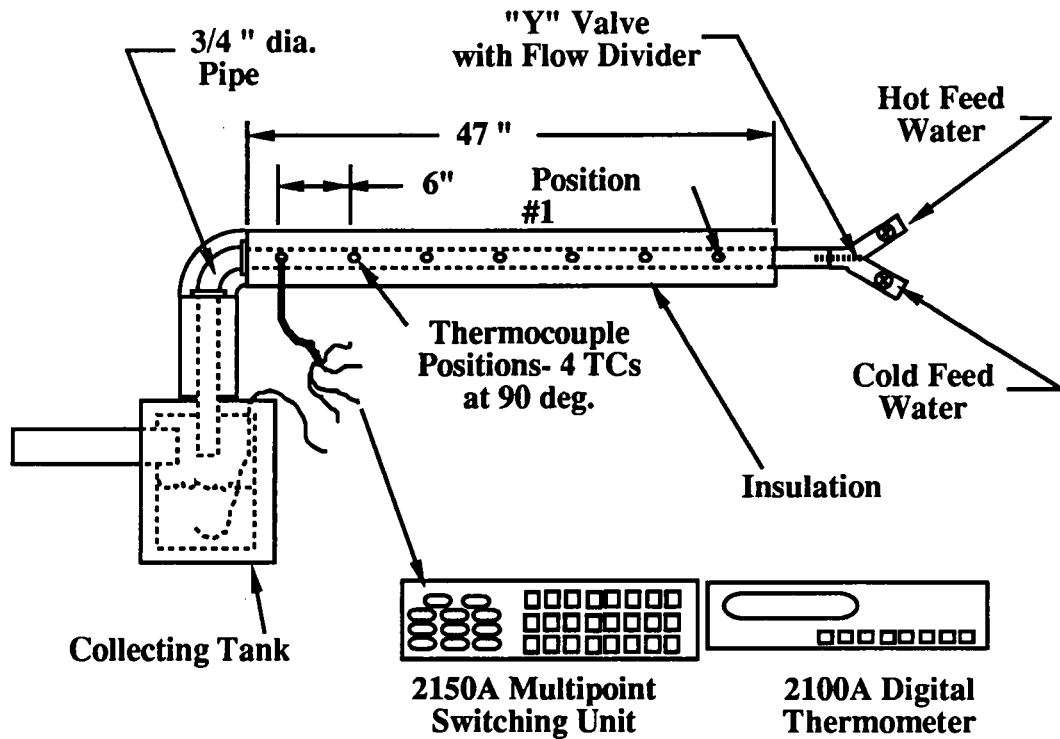


Figure 3.1 Experimental Apparatus

The straight divider is constructed from an aluminum sheet with a thickness of 1/16 inch (see Figure 3.2). The divider is 2 inches in length and 27/32 inches width. The inner pipe diameter is approximately 7/8 inch. The small clearance between the divider and the pipe wall restricts fluid mixing until the flow enters the pipe. One end of the divider is contoured for mounting inside the 'Y' fitting. After mounting, the divider extends approximately three-quarters of an inch into the pipe. The straight divider is intended to restrict the mixing of the hot and cold feed water by directing the flow axially into the pipe. The expected stratification patterns should limit mixing due to the axial nature of the flow.

The angled divider is constructed from the same material as the straight divider (see Figure 3.3). At the end of the angled divider, the corners are bent clockwise at an angle of 45 degrees to induce fluid rotation. Rotating the inlet fluids will produce different levels of stratification. Induced fluid rotations are also common in piping systems when the fluid encounters a bend in the pipe.

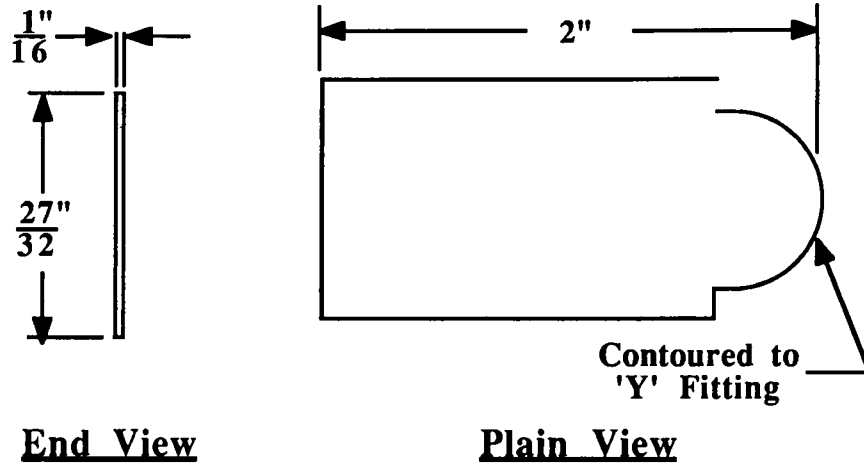


Figure 3.2 Straight Flow Divider Detail

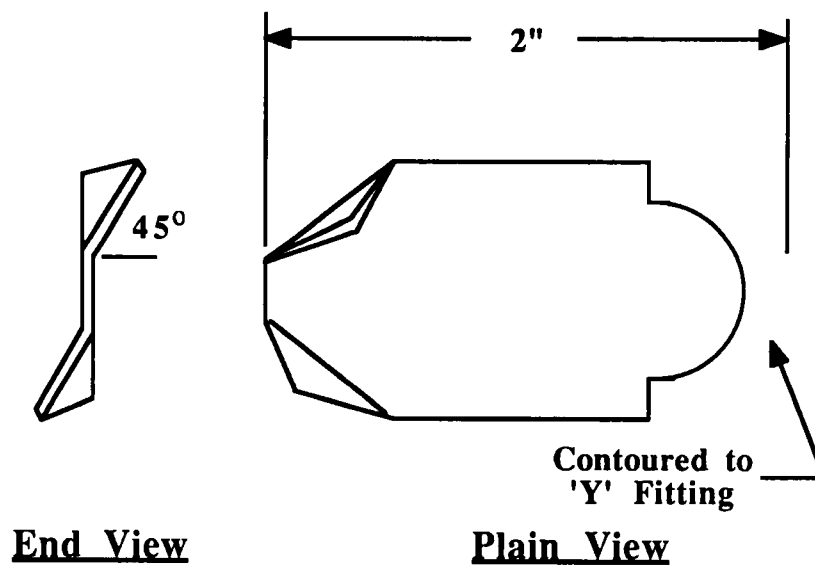


Figure 3.3 Angled Flow Divider Detail

The helical divider, constructed from carbon steel as shown in Figure 3.4, is intended to increase the rotation of the hot and cold feed water. The expected results are a highly stratified fluid flow that has a higher potential for mixing as the flow progresses axially.

Piping Modifications. The final system modification is shown in Figure 3.5. The modification consists of a 90° ell and a 1 inch nipple located between the 'Y' fitting and the horizontal section of pipe. The 'Y' fitting for these experiments contains the straight divider. By using a straight divider, variations in the surface temperature can be compared with the angled and helical dividers.

Variations in Feed Water Temperatures and Flow Rates

The temperature difference between the hot and cold feed water is determined by controlling the temperatures of the hot and cold feed water streams. By varying the temperatures of the feed water sources, the effect of mixing and stratification can be explored. The flow rate of each feed water stream can also be varied. Since the bulk temperature of a fluid is defined in terms of the mass flow rate, a change in the flow rate of one source will change the bulk temperature of the mixed fluid. Given a constant feed water temperature difference, varying the flow rate changes the amount of energy being transported in each feed water source.

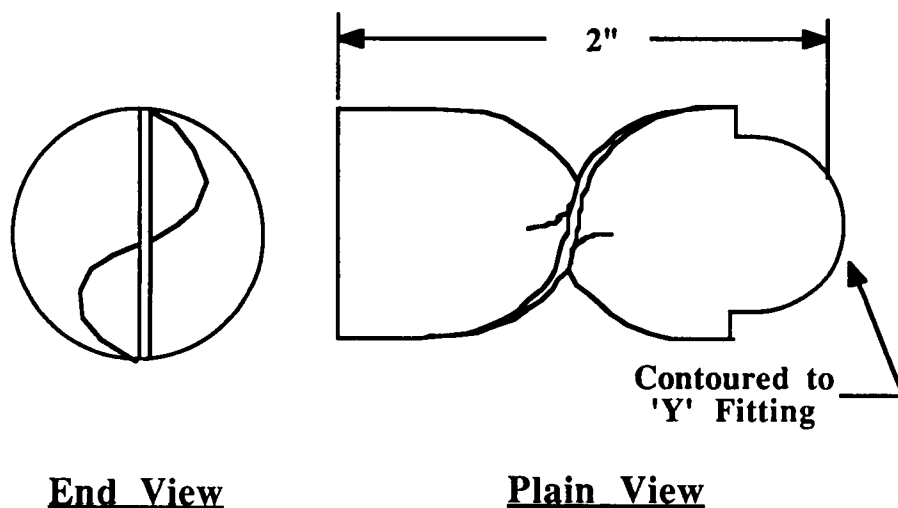


Figure 3.4 Helical Flow Divider Detail

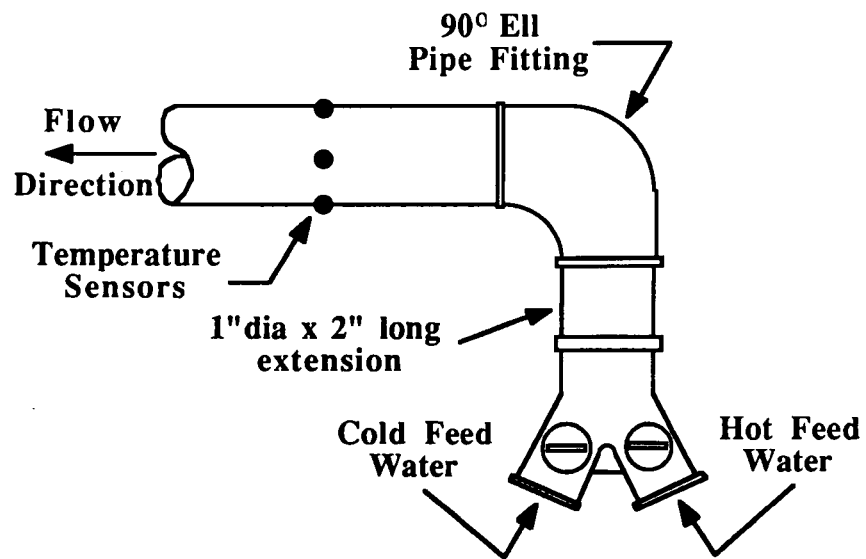


Figure 3.5 Apparatus Modification Using 90° Ell Pipe Fitting

Chapter 4

EXPERIMENTAL AND COMPUTATIONAL RESULTS

Introduction

This chapter presents the results of 31 stratified fluid flow experiments described in Chapter 2. The results illustrate the ability of the estimating process to estimate the bulk fluid temperature. The results are also used to evaluate the performance of three alternate techniques for generating the axial temperature profiles that are used in the estimation process. A sensitivity study that relates the error in the estimate of the bulk temperature to the number and position of the surface temperature measurements is also presented.

Equilibrium Temperature Drop Across the Pipe Wall

In phase III of the estimation process, the temperature drop between the fluid and the exterior pipe surface is subtracting from the average asymptotic value. Three experiments investigate this temperature difference using three different fluid temperatures. The experiments use only one feed water source to ensure a steady fluid temperature and flow rate. The feed water temperatures used in the experiments are 70°F, 85°F, and 110°F.

The experimental results show that the temperature drop across the pipe wall is 0.1°F (+/- 0.05°F) in all cases. Theoretical analysis indicates that the temperature drop across the pipe wall for each condition should not be identical. Considering the precision of the measurement equipment, this result is expected. Therefore, a temperature drop across the pipe wall of 0.1°F will be used for the analysis all of the experiments.

Stratified Fluid Flow Experimental Results

The experiments use three dividers, various hot and cold feed water temperatures, and various feed water flow rates to achieve different levels of stratification. Since the primary cause of stratification is the flow divider, the results are presented according to the

type of divider used in each experiment. For each flow divider, the surface temperatures measured during each experiment are analyzed using each profile technique. Therefore, for each experiment there will be three estimates of the bulk fluid temperature. After the results of the three profile techniques are presented, the performance of each profile method is ranked according to the accuracy of each estimate.

Bulk Temperature Estimates Using Straight Divider

Eight experiments were conducted using the straight divider. As expected, the straight divider produced axial temperature gradients that approach the bulk temperature of the fluid. The results of the bulk temperature estimates obtained from using the three profile methods are similar.

Position Profile Method. The position profile method is applied to the temperature measurements of the eight experiments. In the experiments using the straight divider, the temperature profiles generally exhibit both increasing and decreasing axial changes in surface temperature. Each measured profile approaches to within $\pm 1^\circ\text{F}$ of the measured bulk temperature, which illustrates the convergence of the stratified fluid to an equilibrium temperature. The temperature profiles from Experiment 1 using the position profile method are shown in Figure 4.1. The surface temperature measurements and experimental parameters for each experiment are listed in Appendix C. The asymptotic values of the position profiles are given in Table 4.1 with the measured (actual) bulk temperature, T_{mb} , and the estimate of the bulk temperature, T_{eb} . The asymptotic values of the temperature profiles do not approach the same temperature, but when averaged and the temperature drop across the pipe wall is accounted for, the average error in the estimate of the measured bulk temperature is 0.19°F ($\pm 0.05^\circ\text{F}$).

Ordered Profile Method. Using the measured temperatures from Experiment 1, the ordered profile method produces profiles that are shown in Figure 4.2. The asymptotic value of the ordered profiles is given in Table 4.2, along with the estimate of the bulk temperature. The extrapolated profiles do not approach the same temperature. However, the estimate of the bulk temperature on average is within 0.19°F ($\pm 0.05^\circ\text{F}$) of the measured bulk temperature.

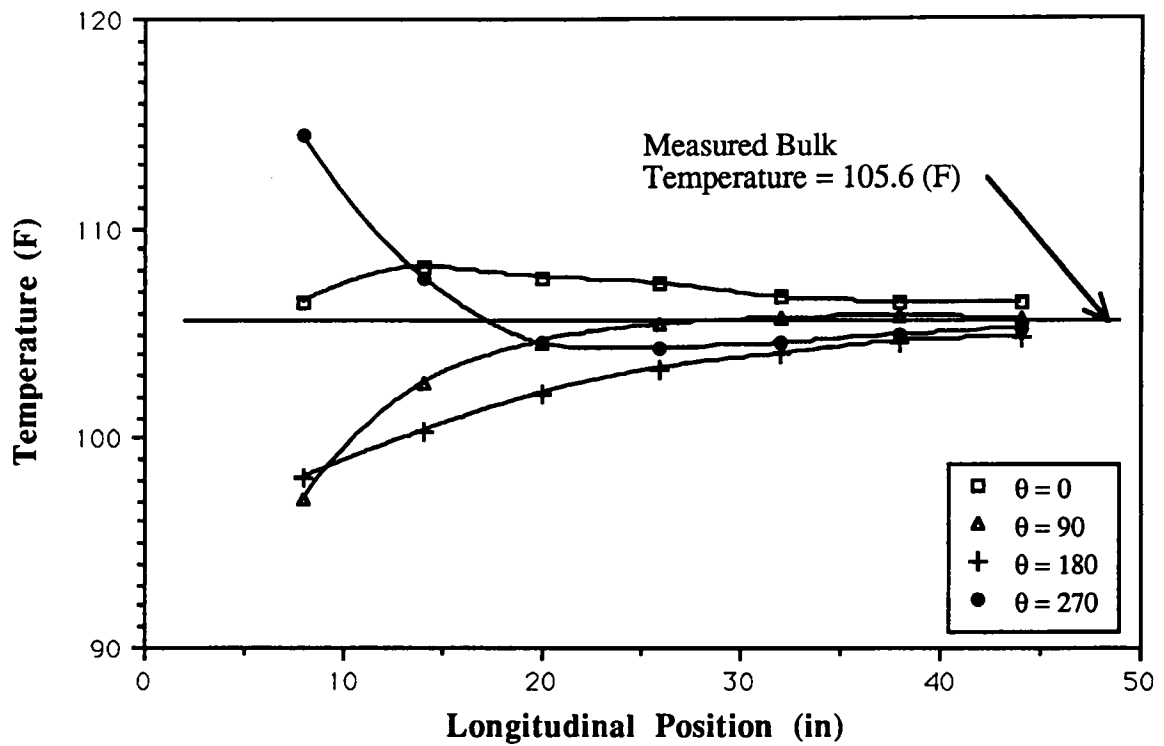


Figure 4.1 Experiment 1 - Profiles Using Position Method and Straight Divider

Table 4.1 Bulk Temperature Estimates Using the Position Profile Method

Experiment No.	Circumferential Position				T_{eb} Estimate	T_{mb} Measured
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$		
1	106.9	108.4	106.0	101.5	105.80	105.6
2	108.3	110.2	107.8	103.1	107.45	107.3
3	106.5	106.6	107.4	107.6	107.13	107.0
4	116.5	117.6	116.1	113.8	116.10	116.3
5	90.7	91.4	92.2	91.9	91.65	91.5
6	119.0	121.6	119.6	117.1	119.43	119.6
7	125.0	125.0	124.5	125.3	125.05	125.3
8	99.5	99.7	99.4	99.0	99.50	99.8

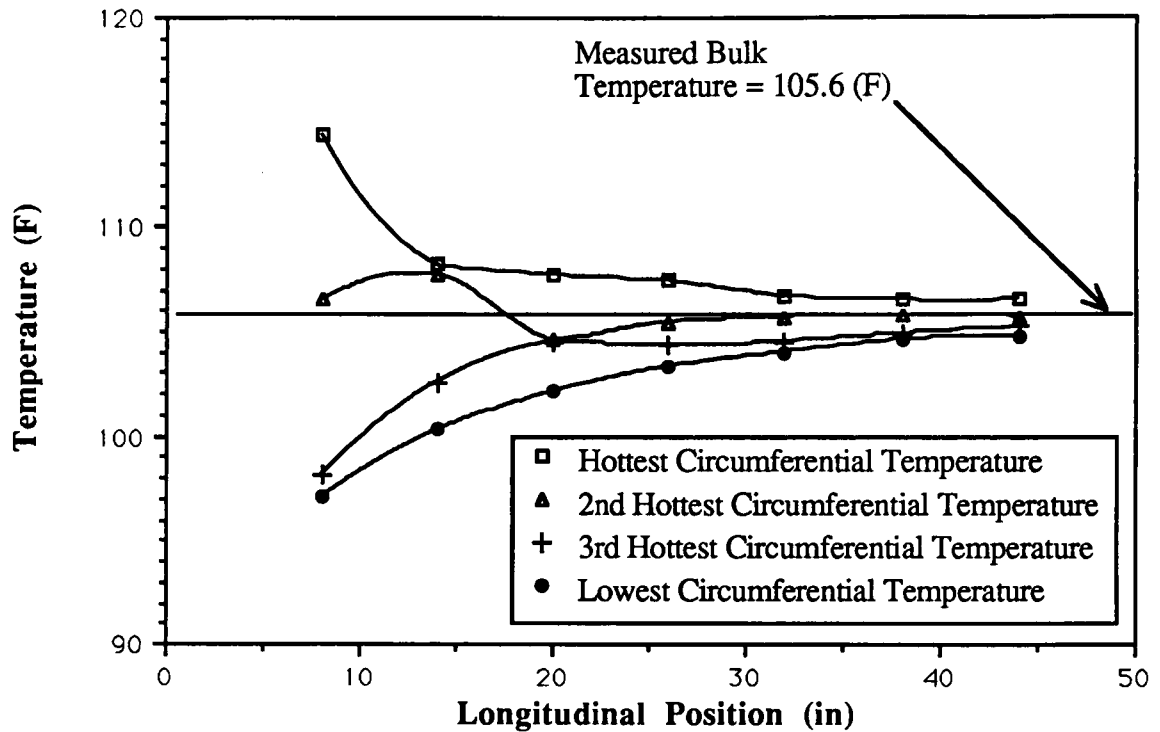


Figure 4.2 Experiment 1 - Profiles Using Ordered Method and Straight Divider

Table 4.2 Bulk Temperature Estimates Using the Ordered Profile Method

Experiment No.	Circumferential Ranking				T _{eb} Estimate	T _{mb} Measured
	Hot	Warm	Cool	Cold		
1	104.3	105.2	107.0	106.3	105.80	105.6
2	105.6	106.8	109.1	108.0	107.40	107.3
3	106.5	106.5	107.5	107.6	107.10	107.0
4	115.8	115.8	115.2	116.8	116.00	116.3
5	90.8	91.5	91.9	91.9	91.60	91.5
6	119.4	118.6	119.6	119.6	119.40	119.6
7	125.1	125.0	124.9	124.9	125.10	125.3
8	99.5	99.2	99.4	99.5	99.50	99.8

Average Profile Method. The temperature profiles from Experiment 1 using the average profile method are shown in Figure 4.3. The average sensor ring temperatures are listed in Appendix C. The asymptotic values of the average profiles are given in Table 4.3 with the computed bulk temperature estimates. The bulk temperature estimates using this approach require computing the asymptotic value of only one profile. The average error between the measured and computed bulk temperature is 0.16°F ($\pm 0.05^{\circ}\text{F}$).

The results of the position profile method given in Table 4.1 show that the computed asymptotic values do not converge to the same value. This is also true for the values computed using the ordered profile method given in Table 4.2. Considering the deviations of the individual values from the measured bulk temperature, the deviations are less using the ordered profile method. The larger deviations using the position method results from a slight swirl of the fluid as shown in Figure 4.1 in the $\theta=0^{\circ}$ and $\theta=270^{\circ}$ profiles. Using the position profiles, the maximum deviation of a single asymptotic value from the bulk temperature is 4.1°F and 1.9°F for the ordered profiles. However, the average error in the bulk temperature estimate is less when using the average profile method. Comparing the three methods, the average profile method results in the best estimate of the bulk temperature as shown in Table 4.4.

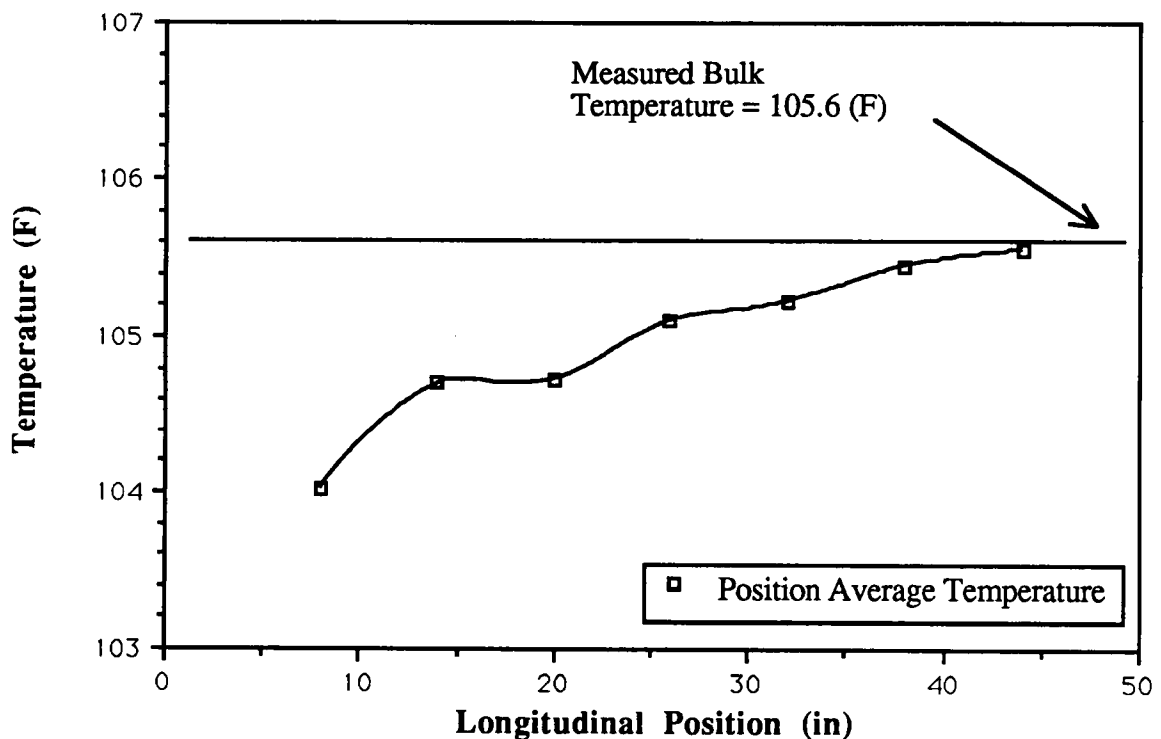


Figure 4.3 Experiment 1 - Profiles Using Position Average Method and Straight Divider

Table 4.3 Bulk Temperature Estimates Using the Average Profile Method

Experiment No.	T_{eb} Estimate	T_{mb} Measured
1	105.61	105.6
2	107.36	107.3
3	107.12	107.0
4	116.08	116.3
5	91.62	91.5
6	119.45	119.6
7	125.00	125.3
8	99.51	99.8

Table 4.4 Bulk Temperature Error Statistics Using Straight Divider

Profile Method	Average Absolute Error	Average Absolute % Error	Standard Deviation
Position	0.19	0.18%	0.06
Ordered	0.19	0.17%	0.08
Average	0.16	0.14%	0.10

Bulk Temperature Estimates Using Angled Divider

The angled divider produces swirling of the inlet hot and cold feed water, resulting in an increase in flow stratification and mixing potential. Six experiments were conducted using the angled divider. As expected, the results of using the angled divider are axial temperature profiles that indicate a swirling fluid. The axial temperature profiles show that as the flow continues through the pipe, surface temperatures are approaching equilibrium.

Position Profile Method. The temperature profiles generated from Experiment 9 using the position method are shown in Figure 4.4. The surface temperature measurements and experimental parameters for each experiment are listed in Appendix C. The asymptotic values of the position profiles are given in Table 4.5, along with the computed bulk temperature estimate. The temperature profiles do not approach the same bulk temperature, but the estimate of the bulk temperature is within 0.25°F ($\pm 0.05^{\circ}\text{F}$) of the measured bulk temperature. This result is similar to the previous results, but the profiles are noticeably different.

Ordered Profile Method. The temperature profiles generated from Experiment 9 using the ordered profile method are shown in Figure 4.5. The asymptotic values computed using the ordered profile method are given in Table 4.6, along with the computed and measured bulk temperature. The average bulk temperature estimate error is 0.25°F ($\pm 0.05^{\circ}\text{F}$).

Average Profile Method. The temperature profiles generated from Experiment 9 using the average profile method are shown in Figure 4.6. The average temperature of each sensor is listed in Appendix C. The asymptotic value of the average profiles is given in Table 4.7 along with the computed bulk temperature estimate. The bulk temperature estimates using this approach require computing the asymptotic value of one profile. The average error between the measured and computed bulk temperature is 0.24°F ($\pm 0.05^{\circ}\text{F}$).

Comparing the three profile methods, the position profile method, and the ordered profile method produced average estimate errors of 0.25°F ($\pm 0.05^{\circ}\text{F}$), respectively, and the average profile method produced an average estimate error of 0.24°F ($\pm 0.05^{\circ}\text{F}$). Again, the average profile method results in the most accurate estimates of the bulk temperature.

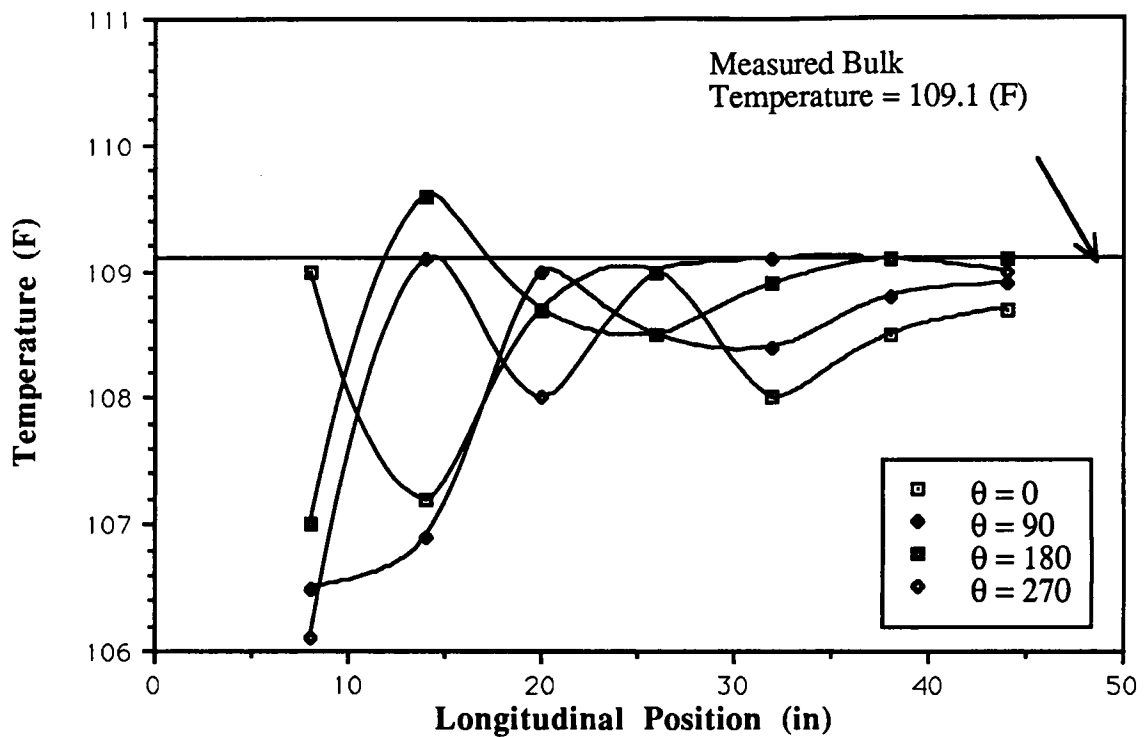


Figure 4.4 Experiment 9 - Profiles Using Position Method and Angled Divider

Table 4.5 Bulk Temperature Estimates Using the Position Profile Method

Experiment	Circumferential Ranking				T_{eb}	T_{mb}
No.	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	Estimate	Measured
9	108.3	109.4	109.5	109.8	109.35	109.1
10	108.4	109.6	109.6	109.8	109.45	109.2
11	109.2	108.9	110.2	109.4	109.53	109.3
12	108.1	108.5	108.3	108.5	108.45	108.7
13	126.8	127.4	127	126.7	127.08	127.3
14	125.1	125.4	124.5	124.7	125.03	125.3

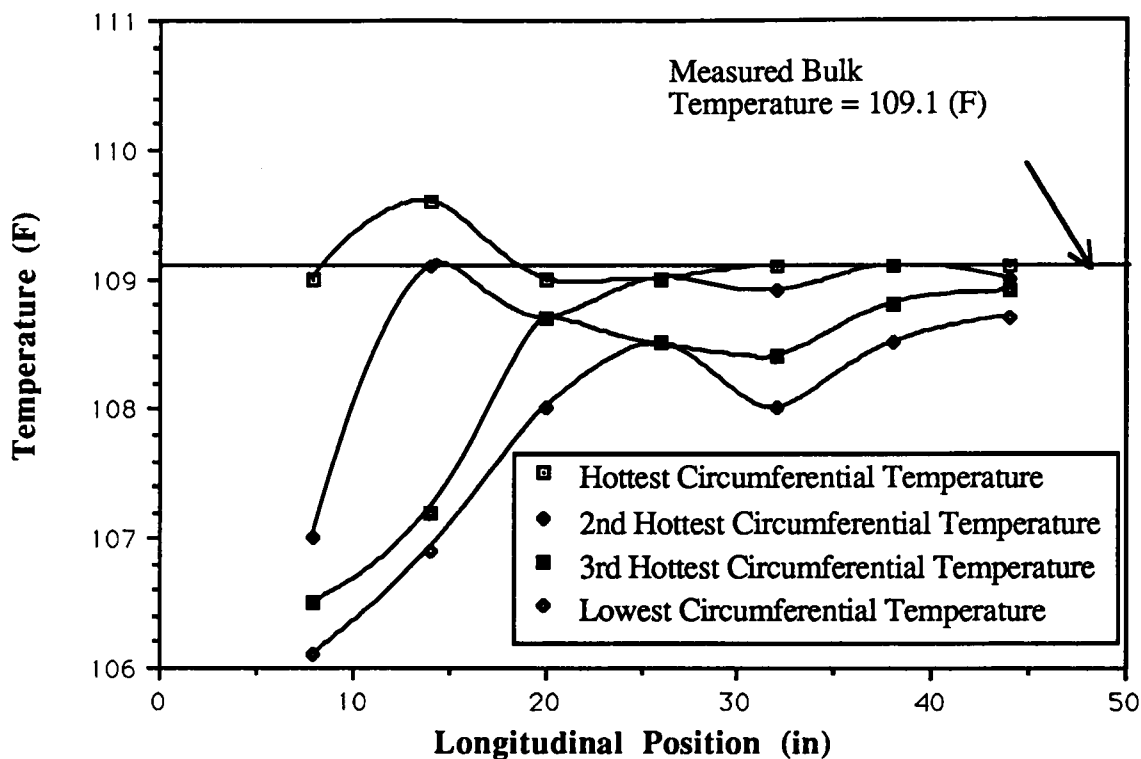


Figure 4.5 Experiment 9 - Profiles Using Ordered Method and Angled Divider

Table 4.6 Bulk Temperature Estimates Using the Ordered Profile Method

Experiment	Circumferential Position				T _{eb}	T _{mb}
No.	Hot	Warm	Cool	Cold	Estimate	Measured
9	109	109.5	109.3	109.1	109.33	109.1
10	109.2	109.7	109.6	109	109.48	109.2
11	109.4	109.5	109.3	109.6	109.55	109.3
12	108.8	108.5	108.1	108	108.45	108.7
13	126.9	126.9	127	127.1	127.08	127.3
14	125.1	125.2	124.8	124.7	125.05	125.3

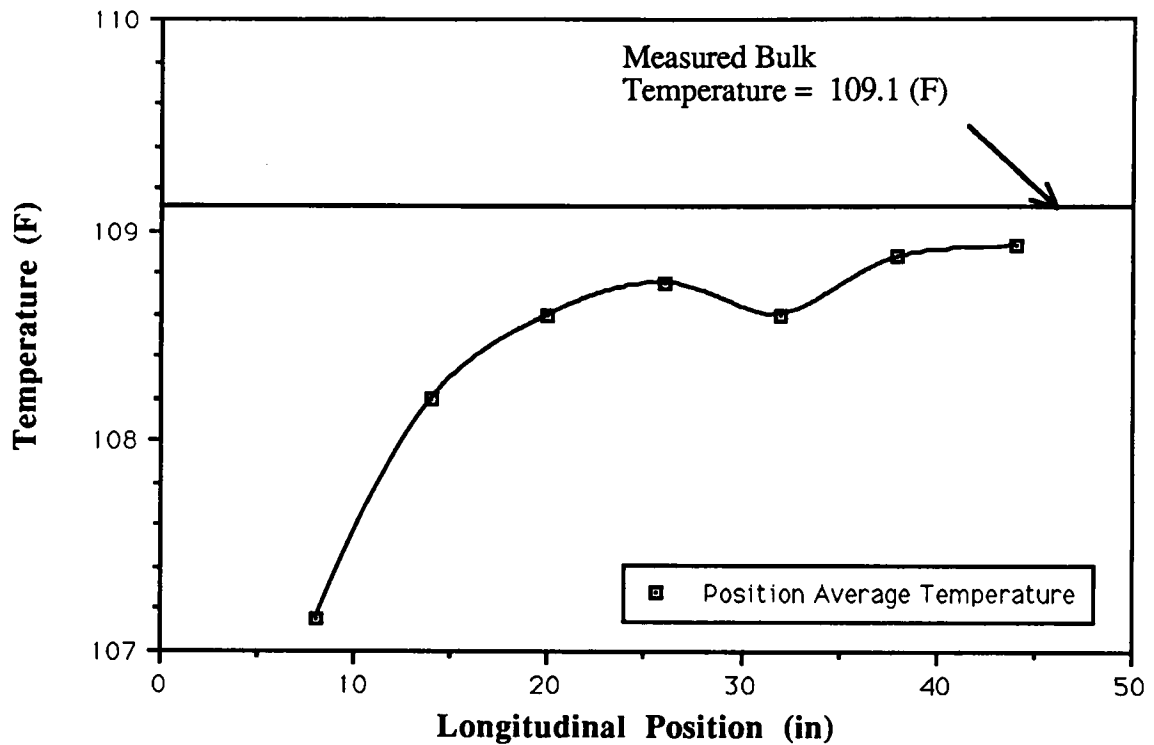


Figure 4.6 Experiment 9 - Profiles Using Position Average Method and Angled Divider

Table 4.7 Bulk Temperature Estimates Using the Position Average Method

Experiment	T_{eb}	T_{mb}
No.	Estimate	Measured
9	109.33	109.1
10	109.46	109.2
11	109.53	109.4
12	108.44	108.7
13	127.07	127.3
14	125.08	125.3

Table 4.8 Bulk Temperature Error Statistics Using Angled Divider

Profile Method	Average Absolute Error	Average Absolute % Error	Standard Deviation
Position	0.25	0.21%	0.02
Ordered	0.25	0.22%	0.02
Average	0.24	0.21%	0.02

Bulk Temperature Estimates Using Helical Divider

The Helical divider is designed to increase swirling of the inlet hot and cold feed water even more than the angled divider resulting in an increase of flow stratification and mixing potential. Sixteen experiments were conducted using the helical divider. The collective results are similar. The helical divider produced axial temperature profiles that oscillate around the bulk temperature of the fluid while the magnitude of the oscillate decays axially.

Position Profile Method. The temperature profiles generated from Experiment 15 using the position method are shown in Figure 4.7. The surface temperature measurements and experimental parameters for each experiment are listed in Appendix C. The asymptotic value of the position profiles is given in Table 4.7 along with the computed bulk temperature estimate. The asymptotic values of each profile do not approach the same bulk temperature, but when averaged and corrected for the temperature drop across the pipe, they estimate the bulk temperature to within 0.14°F ($\pm 0.05^{\circ}\text{F}$) of the bulk temperature.

Ordered Profile Method. The temperature profiles generated from Experiment 15 using the ordered profile method are shown in Figure 4.8. The asymptotic value of the ordered profiles are given in Table 4.8 along with the computed bulk temperature estimate. The average bulk temperature estimate error is 0.14°F ($\pm 0.05^{\circ}\text{F}$).

Average Profile Method. The temperature profiles generated from Experiments 15 using the average profile method are shown in Figure 4.9. The average temperature of each sensor is listed in Appendix C. The asymptotic value of the average profiles is given in Table 4.9 along with the computed bulk temperature estimate. The bulk temperature estimates using this approach require computing the asymptotic value of one profile and correcting this value for the temperature drop across the pipe wall. Averaging the error between the measured and computed bulk temperature reveals an average error of 0.13°F .

Comparing the three methods, the position method and the ordered method produce estimate errors of 0.14°F , and the average position method error is 0.13°F (0.12%).

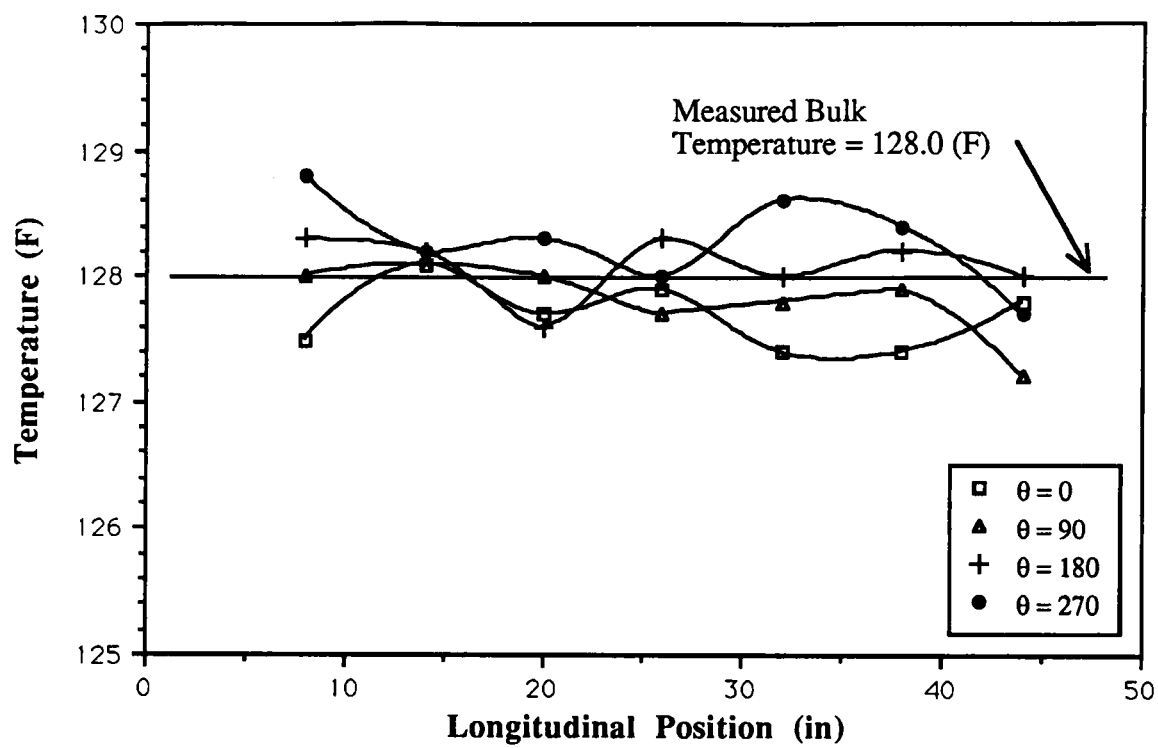


Figure 4.7 Experiment 15 - Profiles Using Position Method and Helical Divider

Table 4.9 Bulk Temperature Estimates Using the Position Profile Method

Experiment	Circumferential Position				T_{eb}	T_{mb}
No.	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	Estimate	Measured
15	127.7	127.6	127.9	127.7	127.83	128.0
16	128.6	128.8	128.5	128.3	128.65	128.7
17	128.2	128.6	128.4	128.1	128.43	128.6
18	128.4	128.6	128.4	128.2	128.50	128.7
19	108.3	108.2	108.3	107.9	108.28	108.5
20	107.5	107.5	107.4	107.2	107.50	107.6
21	99.5	99.5	99.4	99.1	99.48	99.6
22	100.2	100.6	100.8	100.9	100.73	100.9
23	106.1	106.1	106.2	106.1	106.23	106.3
24	120.7	120.5	120.5	120.5	120.65	120.7
25	125.9	126	125.9	125.9	126.03	126.2
26	125.7	125.5	125.4	125.6	125.65	125.7
27	126	126.1	125.9	126	126.10	126.2
28	125.8	126.1	125.8	125.9	126.00	126.2
29	103.8	103.3	103.1	102.7	103.33	103.5
30	122.4	122.7	122.1	121.8	122.35	122.5

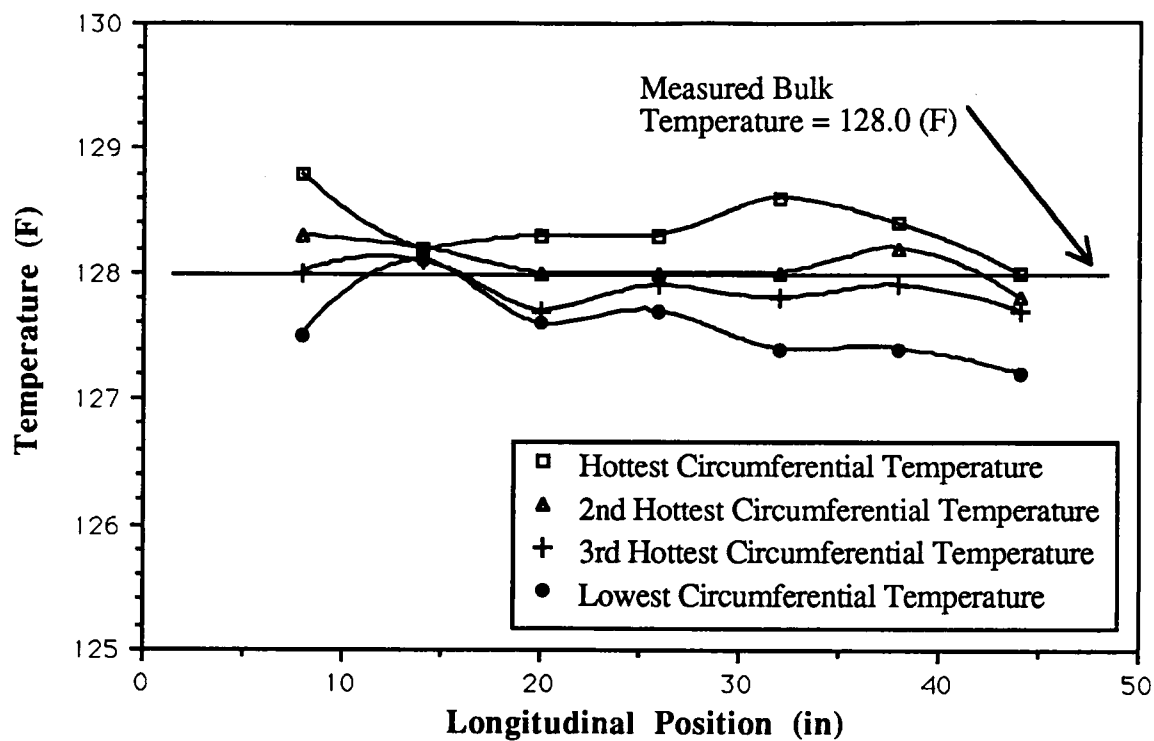


Figure 4.8 Experiment 15 - Profiles Using Ordered Method and Helical Divider

Table 4.10 Bulk Temperature Estimates Using the Ordered Profile Method

Experiment	Circumferential Ranking				T_{eb}	T_{mb}
No.	Hot	Warm	Cool	Cold	Estimate	Measured
15	127.9	127.8	127.6	127.6	127.83	128.0
16	128.8	128.6	128.5	128.3	128.65	128.7
17	128.6	128.6	128.5	128.2	128.58	128.6
18	128.5	128.4	128.5	128.3	128.53	128.7
19	108.4	108.4	108.1	107.8	108.28	108.5
20	107.6	107.5	107.4	107.2	107.53	107.6
21	99.5	99.5	99.4	99.1	99.48	99.6
22	100.9	100.7	100.6	100.2	100.70	100.9
23	106.2	106.1	106.1	106.1	106.23	106.3
24	120.7	120.6	120.5	120.5	120.68	120.7
25	125.9	125.9	126.0	125.9	126.03	126.2
26	125.5	125.5	125.5	125.5	125.60	125.7
27	126.1	126.1	125.3	125.9	125.95	126.2
28	125.9	126.1	125.9	125.6	125.98	126.2
29	103.6	103.3	103.2	102.7	103.30	103.5
30	122.6	122.2	122.1	122.0	122.33	122.5

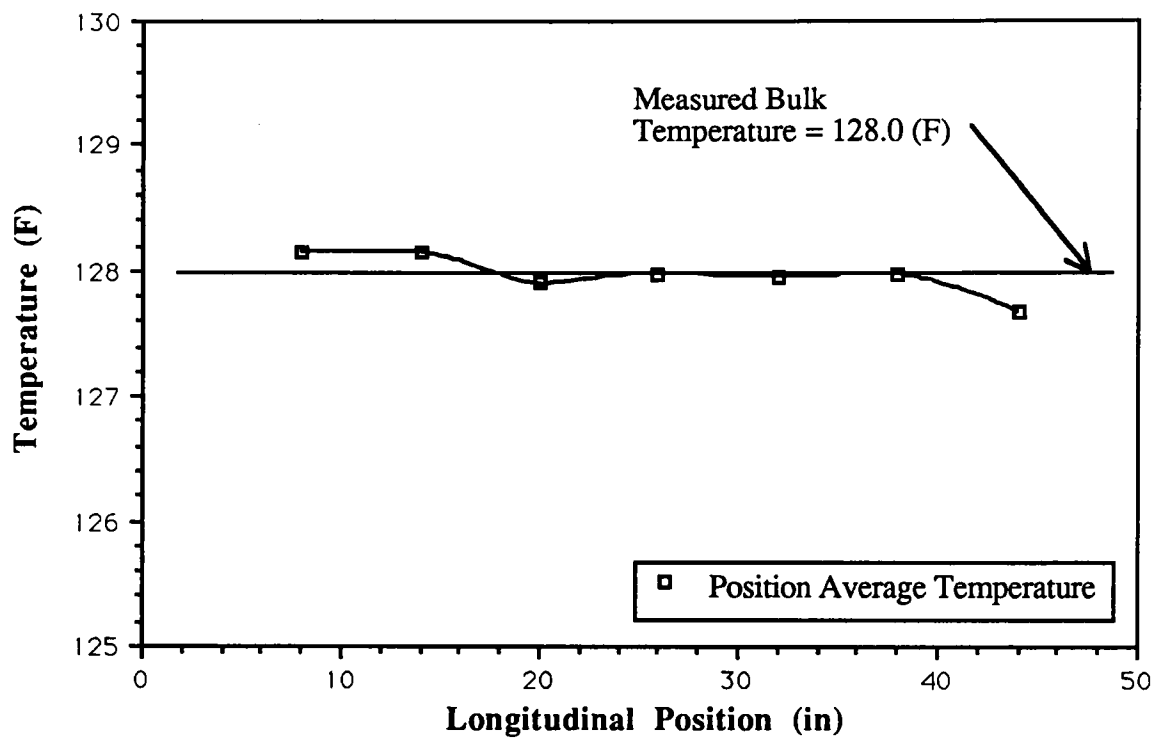


Figure 4.9 Experiment 15 - Profiles Using Position Average Method and Helical Divider

Table 4.11 Bulk Temperature Estimates Using the Position Average Method

Experiment	T_{eb}	T_{mb}
No.	Estimate	Measured
15	127.80	128.0
16	128.65	128.7
17	128.55	128.6
18	128.52	128.7
19	108.28	108.3
20	107.52	107.6
21	99.50	99.6
22	100.71	100.9
23	106.23	106.3
24	120.56	120.7
25	126.00	126.2
26	125.70	125.7
27	126.10	126.2
28	126.00	126.2
29	103.31	103.5
30	122.32	122.5

Table 4.12 Bulk Temperature Error Statistics Using the Helical Divider

Profile Method	Average Absolute Error	Average Absolute % Error	Standard Deviation
Position	0.14	0.12%	0.06
Ordered	0.14	0.12%	0.07
Average	0.13	0.12%	0.07

Bulk Temperature Estimates Using 90° Ell

The addition of a 90° ell is designed to produce swirling of the inlet hot and cold feed water that is common in piping systems. The expected results are an increase in flow stratification and mixing potential. One experiment was conducted using the 90° ell. The 90° ell produced an axial temperature profile that oscillates near the bulk temperature of the fluid.

Position Profile Method. The temperature profiles generated from Experiment 31 using the position method are shown in Figure 4.10. The surface temperature measurements and experimental parameters for each experiment are listed in Appendix C. The asymptotic value of the position profiles is given in Table 4.13, along with the computed bulk temperature estimate. The temperature profiles do not approach the same bulk temperature, but when averaged and corrected for the temperature drop across the pipe, they estimate the bulk temperature to within 0.07°F (+/-0.05°F) of the bulk temperature.

Ordered Profile Method. The temperature profiles generated from Experiment 31 using the ordered profile method are shown in Figure 4.11. The asymptotic value of the ordered profiles is given in Table 4.14, along with the computed bulk temperature estimate. The average bulk temperature estimate error is 0.07°F (+/-0.05°F).

Average Profile Method. The temperature profiles generated from Experiment 31 using the average profile method are shown in Figure 4.12. The asymptotic value of the average profiles is given in Table 4.15, along with the computed bulk temperature estimate. The measured surface temperatures processed using the average position method are listed in Appendix C. Averaging the error between the measured and computed bulk temperature reveals an error of 0.09°F (+/-0.05°F).

Comparing the three methods, the difference in the estimation error is insignificant. A summary of the estimation errors for the three profile methods is given in Table 4.16.

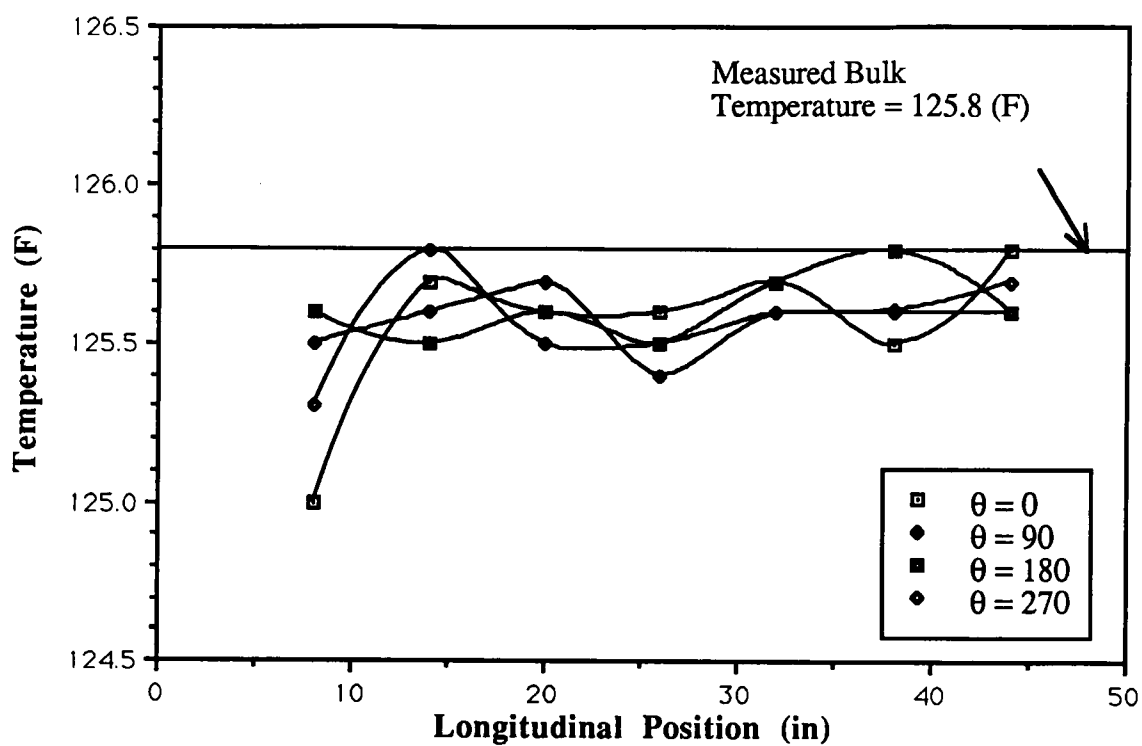


Figure 4.10 Experiment 31 - Profiles Using Position Method and 90° Ell

Table 4.13 Bulk Temperature Estimates Using the Position Profile Method

Experiment No.	Circumferential Position				T_{eb} Estimate	T_{mb} Measured
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$		
31	125.8	125.5	125.6	125.6	125.73	125.8

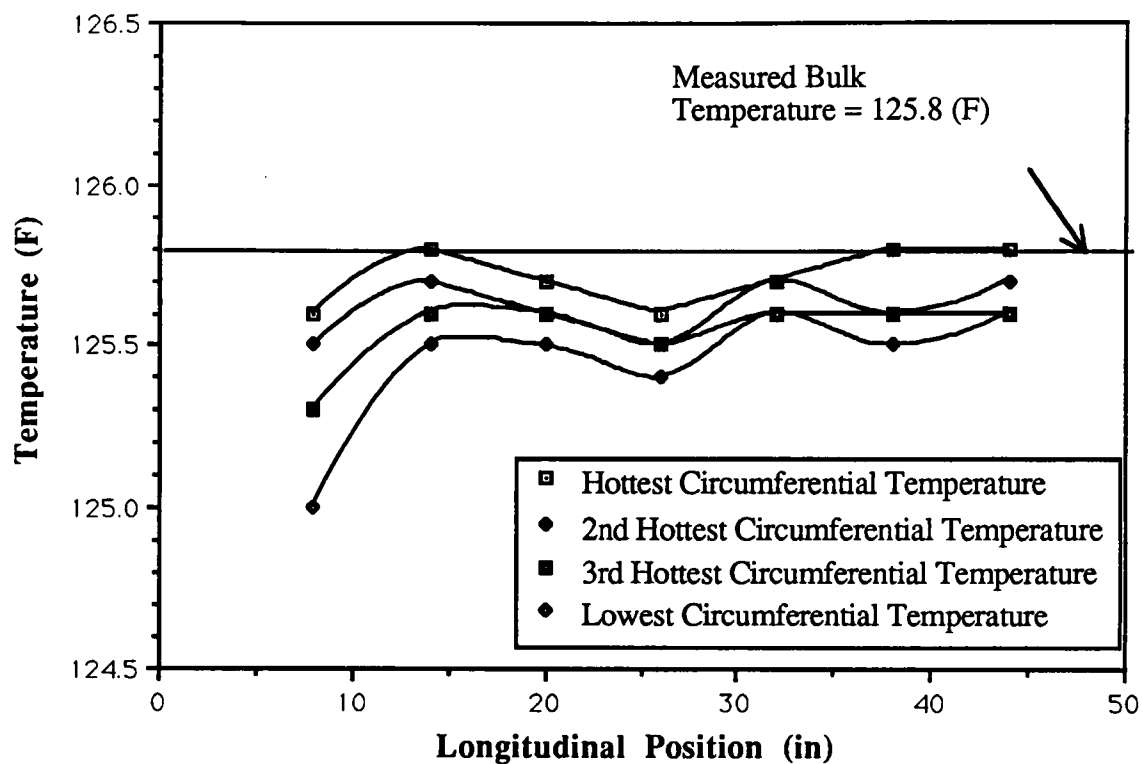


Figure 4.11 Experiment 31 - Profiles Using Ordered Method and 90° Ell

Table 4.14 Bulk Temperature Estimates Using the Ordered Profile Method

Experiment No.	Circumferential Ranking				T _{eb}	T _{mb}
	Hot	Warm	Cool	Cold	Estimate	Measured
31	125.7	125.6	125.6	125.6	125.73	125.8

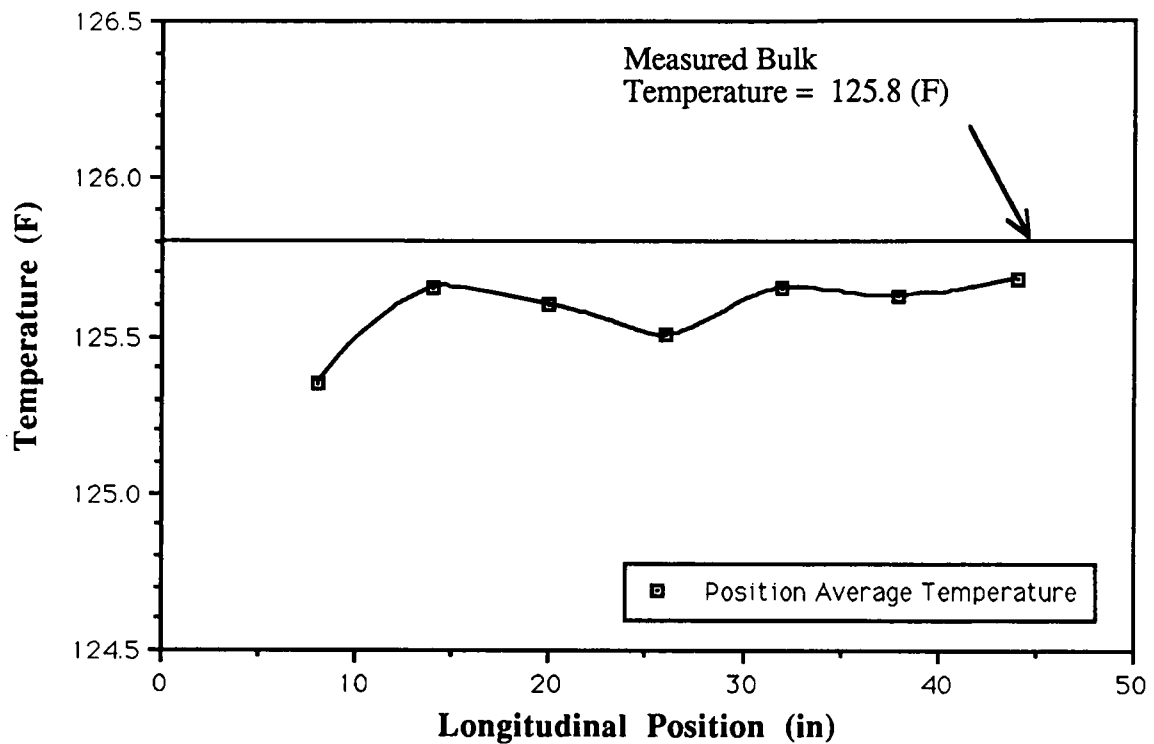


Figure 4.12 Experiment 31 - Profiles Using Average Profile Method and 90° Ell

Table 4.15 Bulk Temperature Estimates Using the Average Profile Method

Experiment	T_{eb}	T_{mb}
No.	Estimate	Measured
31	125.71	125.8

Table 4.16 Bulk Temperature Error Using the Helical Divider

Profile Method	Absolute Error	Absolute % Error
Position	0.07	0.06%
Ordered	0.07	0.06%
Average	0.09	0.07%

Summary of the Profile Methods Results

Three criteria are used to evaluate the accuracy of the estimation process: average error, average percent error, maximum error, and standard deviation. The average error is computed from the results of the 31 experiments. Averaging the error illustrates the overall efficiency of each method given various levels of stratification. The maximum error and standard deviation establishes a bounded confidence interval of the efficiency of each estimate.

The results summarized in Table 4.17 show the average profile method produces more accurate estimates of the bulk fluid temperature compared to the position and ordered profile methods. The average error associated with the position and ordered profile methods is 0.16°F and 0.15°F for the average profile method. The average percent error follows the same trend with 0.014% error for the position and ordered profile methods and 0.13% error for the average profile method. The maximum error of each profile method is 0.3°F. Although the difference between the methods are small, the average profile method will be considered the superior method.

Table 4.17 Summary of Profile Method Estimation Errors

Profile Method	Average Error (F)	Average % Error	Maximum Error (F)	Standard Deviation
Position	0.16	0.14%	0.3	0.04
Ordered	0.16	0.14%	0.3	0.06
Average	0.15	0.13%	0.3	0.06

Estimation Error Using Fewer Surface Temperature Measurements

There are no guidelines for determining the required number and location of the temperature sensors needed to estimate the bulk temperature within a given degree of accuracy. The experimental results show that the required number and position of the sensors are dependent on the stratification level and the mixing of the fluid. For example, given a constant temperature fluid, only one sensor would be required to estimate the bulk temperature. For situations where stratification is present, more temperature measurements are necessary. To investigate the question "how many sensors are necessary?" an analysis is performed using various combinations of the measured surface temperatures from the 31 experiments. This study examines the error associated with varying the number of axial sensor rings and the number of sensors in each ring. The results are presented graphically from tabulated data in Appendix C.

The error in the bulk temperature estimate using 4 sensors at each axial position and a variable number of sensor rings is shown in Figure 4.13. The results have been presented for the analysis using 7 axial positions. For the 6 sensor ring analysis, the sensor ring at the exit end of the pipe is excluded. The development of the remaining sets of analysis is achieved by incrementally excluding the sensor ring that is nearest the exit end of the pipe.

As shown in Figure 4.13, the error in the bulk temperature estimate increases as the number of sensor rings is decreased with the exception of using 6 sensor rings. Figure 4.14 presents the results of using only 3 sensors in each sensor ring. The analysis is based on arbitrarily selecting 3 circumferential sensor positions corresponding to $\theta = 0^\circ$, $\theta = 180^\circ$ and $\theta = 270^\circ$. Once selected, profiles are developed using temperature measurements made at these circumferential locations. The results indicate decreasing error as the number of sensors rings is increased, but the overall error generated using 3 sensors in each ring is greater than using 4 sensors in each ring.

Figure 4.15 presents the results of using 2 sensors in each sensor ring. The analysis is based on arbitrarily selecting 2 circumferential sensor positions corresponding to $\theta = 0^\circ$ and $\theta = 180^\circ$. Once selected, profiles are developed using temperature measurements made at these circumferential locations. The results indicate a further increase in the overall error with the average profile method having the greatest increase in error.

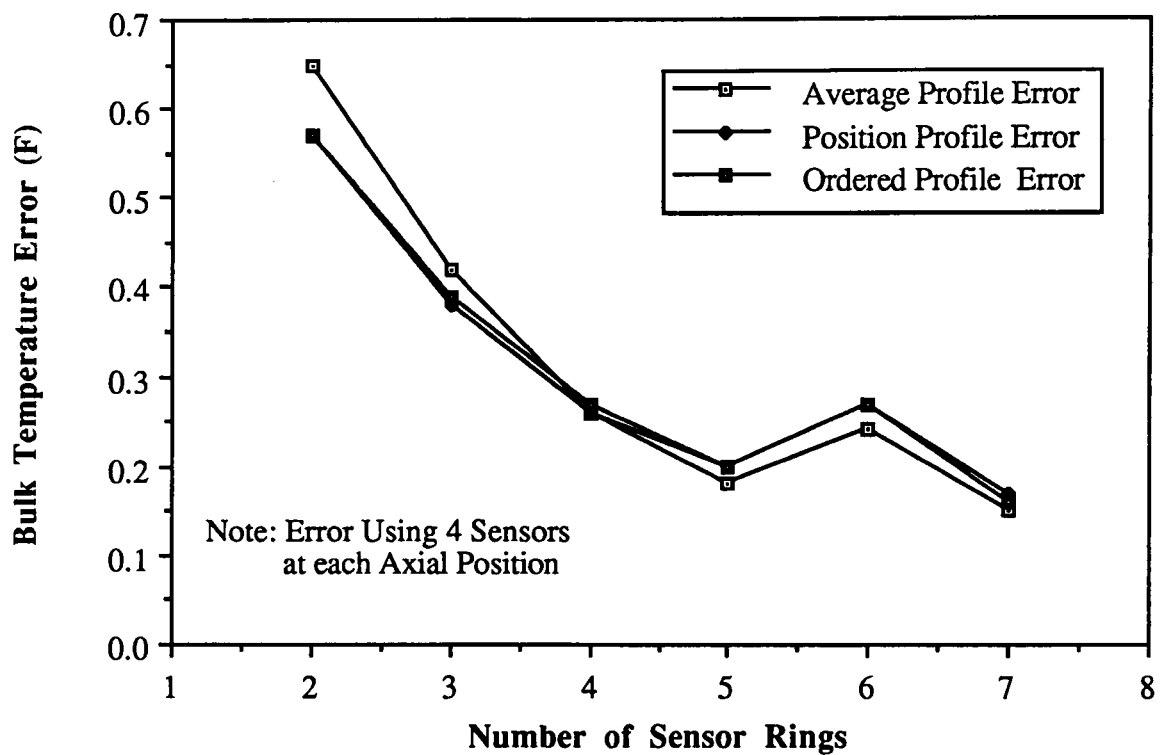


Figure 4.13 Bulk Temperature Estimation Error Using a Variable Number of Axial Sensor Rings

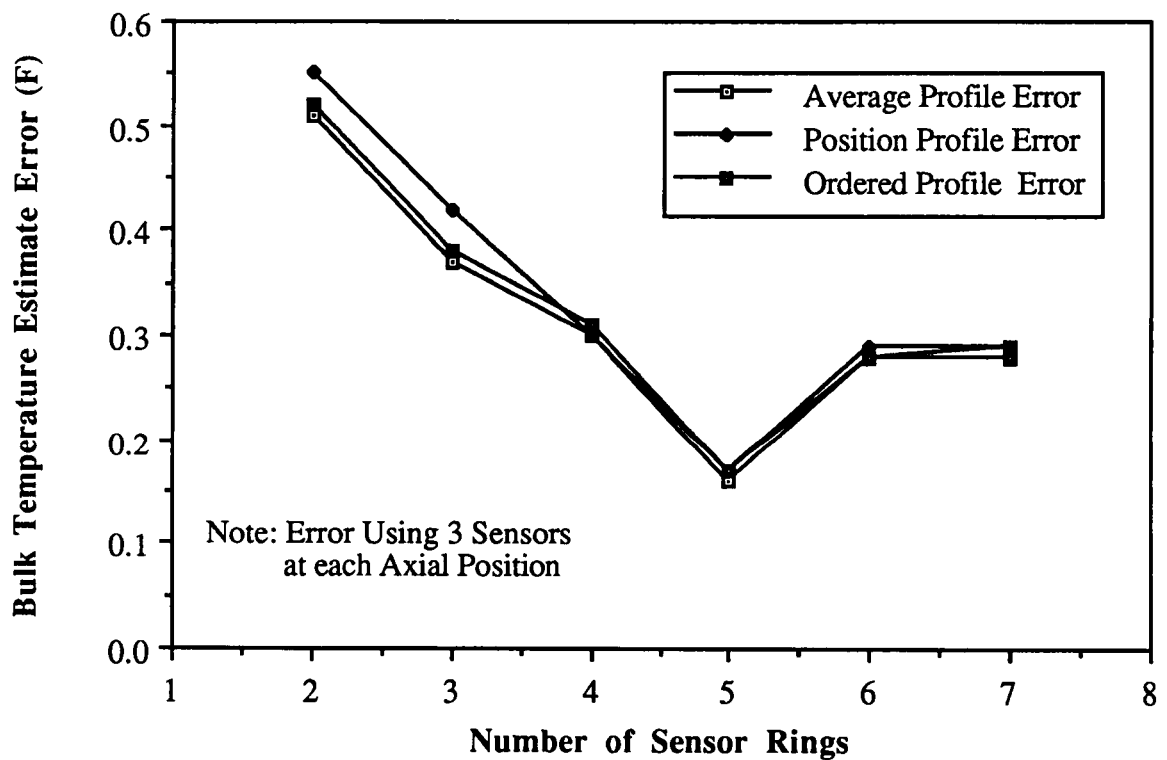


Figure 4.14 Bulk Temperature Estimation Error Using a Variable Number of Axial Sensor Rings with Three Sensors in Each Ring

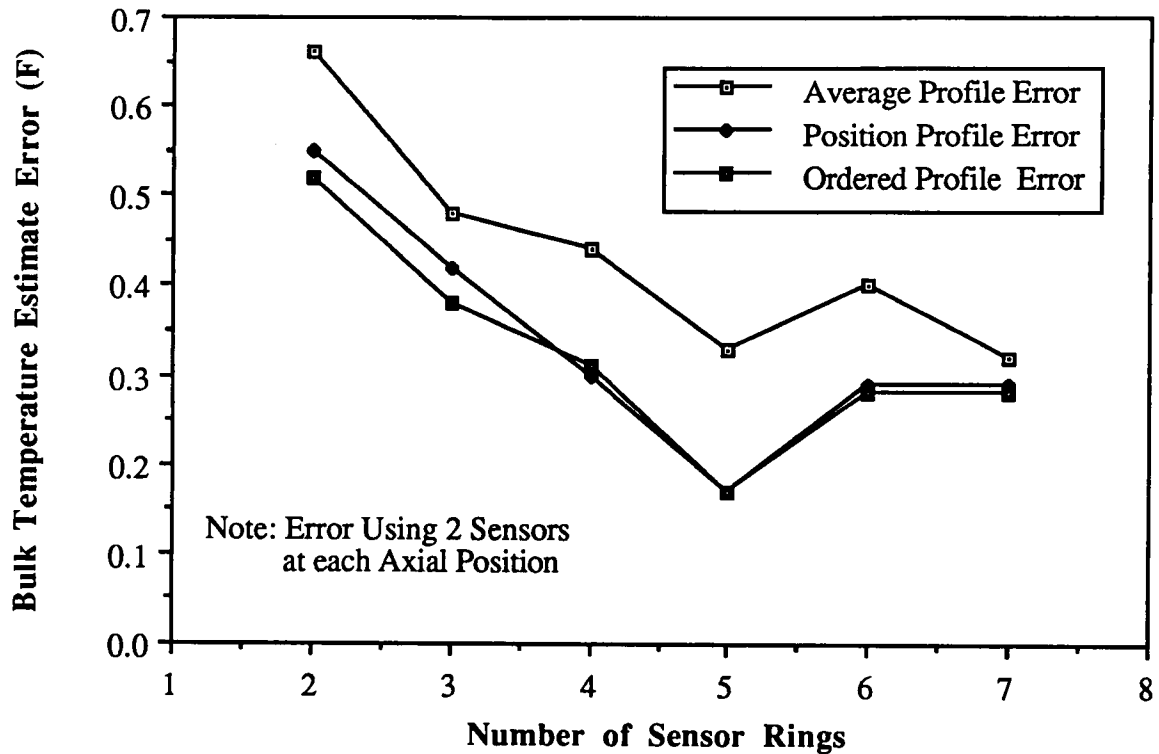


Figure 4.15 Bulk Temperature Estimation Error Using a Variable Number of Axial Sensor Rings with Two Sensors in Each Sensor Ring

Figure 4.16 shows the change in the estimation error using 7 axial sensor rings and a variable number of sensors in each ring: as the number of sensors in each ring is increased, the estimation error reduces significantly. Therefore, as the number of sensors is increased, the error in the estimation decreases. In general, as the number of sensors increases, the error in the estimate approaches an asymptotic value. This trend can be used to experimentally determine the minimum number of sensors required for each application.

Instrumentation and Estimation Error Summary

As the analysis considers more sensors, the error in the bulk temperature estimate decreases. The best estimates of the bulk temperature are produced with data from 28 surface mounted sensors. This result indicates that the decrease in error results from obtaining better estimates of the average surface temperature at each sensor ring location. As illustrated in Figure 4.16, the error decreases significantly as the number of sensors in each sensor ring is increased.

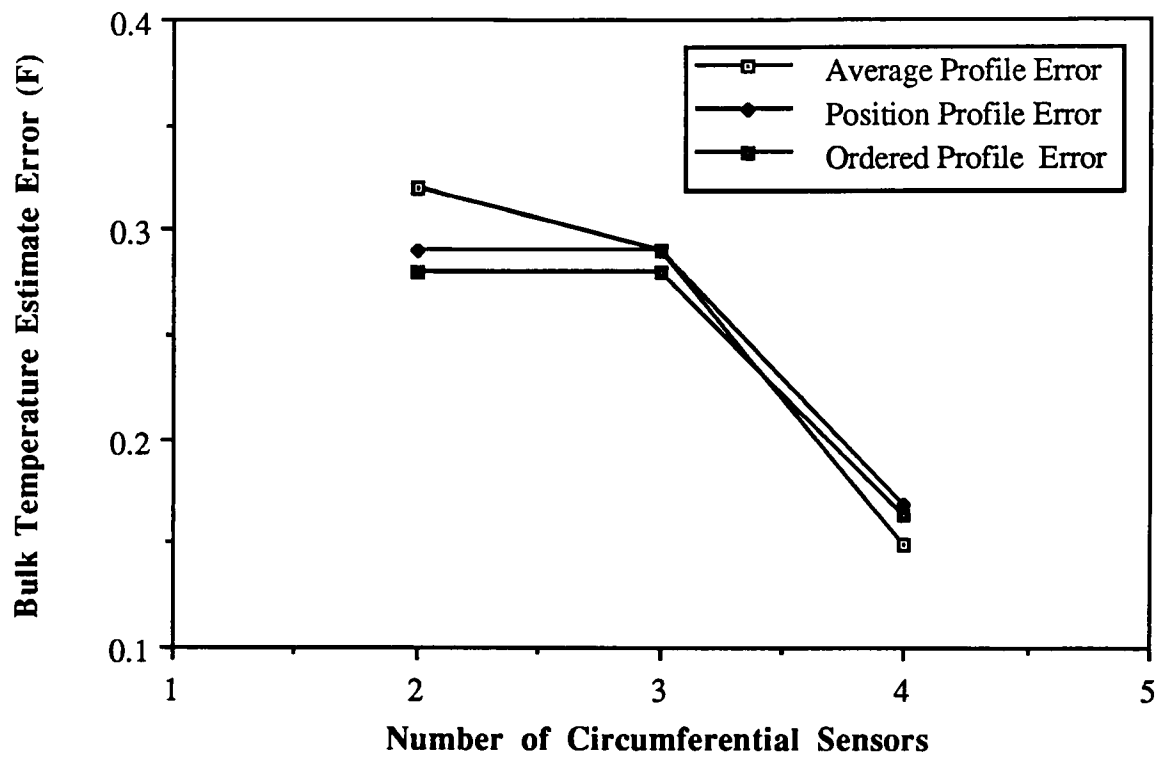


Figure 4.16 Bulk Temperature Estimation Error Using 7 Sensor Rings with a Variable Number of Sensors in Each Sensor Ring

Chapter 5

FURTHERING THE ESTIMATING PROCESS

Introduction

The results presented in Chapter 4 show that the average profile method yields the best estimate of the bulk temperature. This technique relies upon the surface temperature measurements to compute an average temperature at each sensor ring position along the pipe. As shown by the sensitivity analysis presented in Chapter 4, increasing the number of sensors in each sensor ring increases the accuracy of the estimate. Chapter 2 explains how circumferential fluid temperature variations may introduce error into the estimating process. Therefore, given a limitation on the number of temperature measurements, a process was developed that may increase the accuracy of the bulk temperature estimate. Instead of extrapolating the surface temperature profiles, the corresponding *fluid temperatures* are computed at each sensor, and the resulting fluid temperature profiles are used in the estimating process.

This process is based on neural networks created using theoretical solutions. The neural network paradigm, backpropagation, was chosen to develop this relationship because of its proven ability in complex functional mappings [12]. The information required to develop or train the network is a set of inputs (surface temperatures) and corresponding outputs (fluid temperatures). The training information is generated using finite element analysis, FEA. The outcome of the FEA is a set of pipe surface temperatures for each variation in the fluid boundary condition. Once trained, the neural network computes discrete values of the fluid temperature using measured surface temperatures. These fluid temperatures can be used to estimate the bulk temperature. Since the estimation process uses fluid temperatures instead of pipe surface temperatures, the asymptotic value of the axial profiles will be the bulk temperature estimate.

Predicting Fluid Temperatures Using Finite Element Analysis and Neural Networks

The development process has four phases: *Phase I*- the FEA models are generated using properties of the piping system and various fluid boundary conditions, *Phase II*- the FEA is performed and the neural network training sets are generated, *Phase III*- train the neural network, *Phase IV*- process new sets of data and compare the results of actual and predicted fluid temperatures.

Phase I: Developing the Fluid Boundary Conditions

The ability of a trained network to make accurate predictions relies on the information contained in the training set. Therefore, the training set must contain the response of the system to expected changes in the system parameters. Since neural networks perform functional mappings based on the information contained in the training data, two types of conditions are used to develop the fluid boundary conditions. The first generates random fluid temperatures based on the upper and lower fluid temperature limits expected in the flow. The second generates arbitrary fluid temperatures such as constant temperature flows. These temperature profiles may also reflect known characteristics of the flow.

Phase II: Generating Solutions to the Diffusion Equation

The surface temperatures of the pipe are computed from finite element analysis using the fluid temperature profiles from Phase I. The results of the finite element study are sets of solutions to the diffusion equation. From these solutions, the fluid temperature and the corresponding pipe surface temperatures are used to train the neural network.

Phase III: Training the Neural Network

The neural network is designed to accept the surface temperatures as inputs, and the fluid temperatures as the desired outputs. The error between the predicted fluid temperatures and the desired temperatures is used by the algorithm to increase the accuracy of the network. Training the network is an iterative process that is repeated until the prediction error becomes acceptable. The next phase examines the prediction error associated with data sets that were not used during training.

Phase IV: Examining the Trained Network Accuracy

The function of new data sets, called the recall data, is to ensure that the neural network can predict fluid temperatures from an arbitrary surface temperature profile. This procedure begins by processing the recall data using the trained network and examining the prediction error. If the error is acceptable, training is successfully complete. Otherwise, training continues (Phase III) until the recall error is within acceptable bounds. Achieving an acceptable error may require adding more information (data sets) to the training set used in Phase III.

Modeling Hot-Leg Piping of the RCS

There are four phases of developing a neural network model of the diffusion equation using representative properties of the RCS. In *Phase I* the model is defined and the boundary conditions are developed. Several conditions must be considered during development of the finite element models:

1. What are the Geometrical Properties of the Pipe and Insulation ?
2. What are the Characteristics of the Flow?
3. What are the Environmental Boundary Conditions ?

This study uses representative RCS piping properties and measured plant data from a four-loop PWR [2]. The hot-leg pipe is considered to be stainless steel with an outside diameter of 36 inches and a wall thickness of 2". The thickness of the pipe insulation is considered to be 12 inches. Table 5.1 lists the thermal properties of the pipe and insulation.

What are the characteristics of the flow? The temperature distribution of the flow is considered to be steady, based on the hot-leg RTD temperature measurements. Table 5.2 shows the instantaneous temperature measured by three sensors in each of the four hot-legs and a 5 minute average temperature. A comparison of the instantaneous and average temperature shows that the measurements at that position in the flow are relatively constant. It also indicates that the ranking of the fluid temperature between the sensors in each hot-leg remained constant during the measurement period. For example, in hot-leg loop A the temperature measured by T2 is constantly the highest throughout the measurement period. Table A.3 of Appendix A presents a more complete set of hot-leg RTD measurements that was collected during one month of plant operation.

Table 5.1 Representative Hot-leg Piping Properties

Conductivity (Btu/hr ft °F)		Convective Coefficient (Btu/hr ft ² °F)		Temperature (F)	
Pipe	Insulation	Air	Fluid	Air	Fluid
7.5	0.045	7.5	12000.0	100.0	Variable

Table 5.2 Hot-leg RTD Temperature Measurements

Hot-Leg Loop	T1 (F)	T2 (F)	T3 (F)	T1 (F)	T2 (F)	T3 (F)
	Instantaneous			5 minute average		
	6/19/90					
A	609.6	611.0	607.8	609.6	610.9	608.0
B	611.5	605.8	609.8	612.2	604.8	610.0
C	609.9	607.3	611.1	609.8	607.6	610.9
D	608.8	604.6	611.1	609.0	604.7	611.0
	6/22/90					
A	609.7	611.3	608.7	610.0	611.3	608.5
B	612.3	605.9	610.6	612.8	605.4	610.6
C	609.9	608.2	611.5	610.4	608.0	611.4
D	610.7	605.0	611.9	610.0	605.7	612.0
	6/26/90					
A	609.3	611.2	608.2	609.6	611.1	608.0
B	612.6	604.9	610.1	612.4	605.0	610.2
C	609.7	608.4	610.9	610.1	608.0	611.0
D	609.2	604.9	611.4	609.2	605.0	611.3

The boundary condition for the finite element model also uses representative properties and environmental conditions of hot-leg piping. Table 5.1 also lists the thermal properties of the fluid and the ambient environment assumed in the analysis [13]. The convective coefficient for the fluid boundary conditions is computed using equation 5.1 [6].

$$h_f = 160(1 + 0.012 T_f)u^{0.8}/(D_i)^{0.2} \quad (5.1)$$

where T_f is the reference fluid temperature, u is the fluid velocity, and D_i is the inside diameter of the pipe. This equation is based on turbulent flow inside clean tubes. This condition exists in the hot-legs where the Reynolds number is of the order 1×10^6 .

Fifty fluid boundary conditions were generated using both random and arbitrary techniques described previously. The limits imposed on the fluid temperature is ± 5 °F based on an average fluid temperature of 605 °F. From phases II-III, the results of the

finite element models are used to generate training and recall data for the neural network. Thirty-six fluid/pipe surface temperature sets are used for training, and fourteen are used for recall.

Neural Network Training and Recall Results

After 25,000 training iterations, the network was used to predict the fluid temperatures from 14 profiles that had not been used during training. Examples of 4 random fluid profiles and 2 prescribed profiles are shown in Figures 5.1-5.4 and 5.5-5.6, respectively. These figures show that the neural network prediction using the random profiles are in close agreement with the desired profiles. The prediction error from the prescribed profiles is greater than that of the random profiles. This result may indicate that more than 36 prescribed profiles are needed in the training data if better accuracy is desired.

The overall results of the recall data show that the average prediction error of the recalled data is 0.06°F (0.01%). The maximum temperature error is 1.75°F (0.29%), and the average of the maximum error from all input patterns is 0.90°F (0.14%). The recall data and the predicted fluid temperatures are listed in Appendix D. These results show that the trained neural network generalized with a moderate accuracy the fluid/surface temperature relationship based on the diffusion equation.

The neural network program used in this study was ANSIM by the Science Applications International Corporation [14]. The finite element program used in this study is a linear implementation of the diffusion equation using the Galerkin weak statement criterion [15].

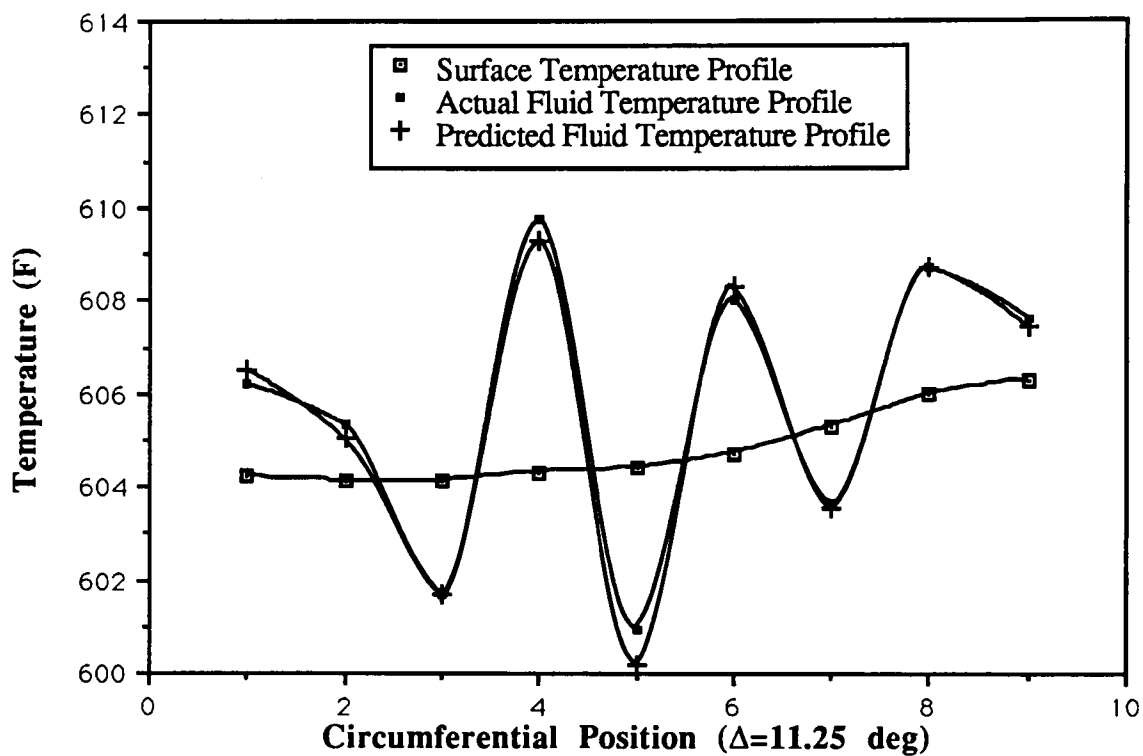


Figure 5.1 Fluid Temperature Profile Prediction Using Random Profile #9

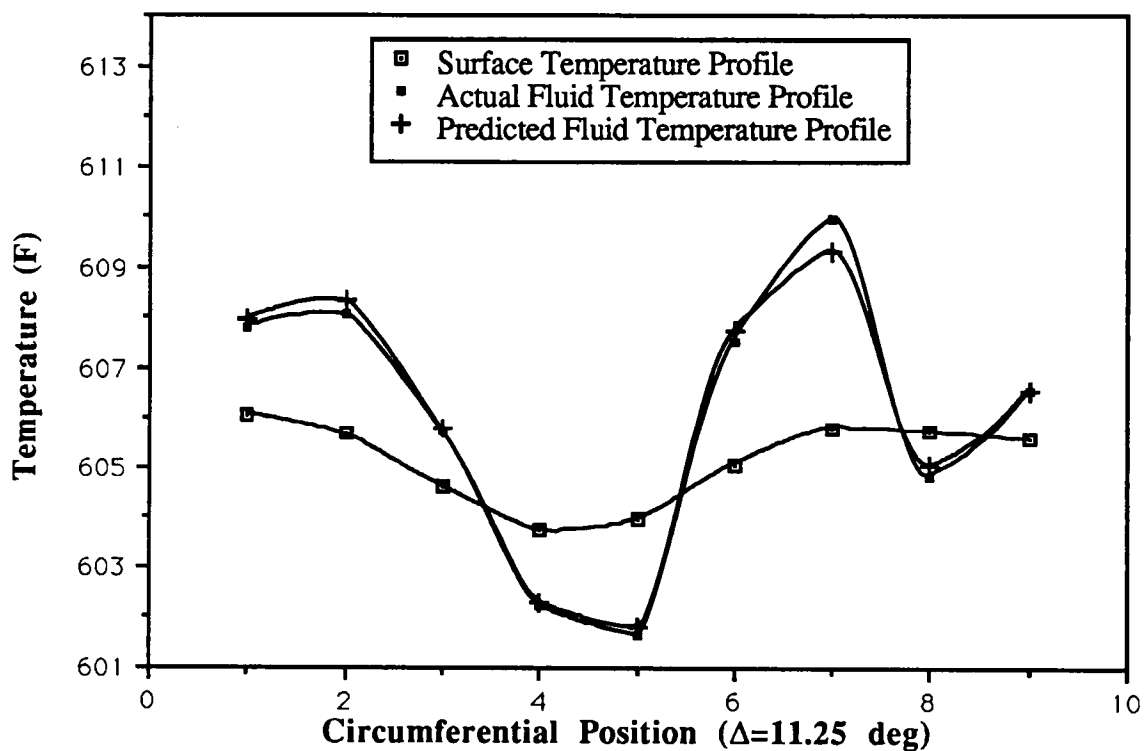


Figure 5.2 Fluid Temperature Profile Prediction Using Random Profile #11

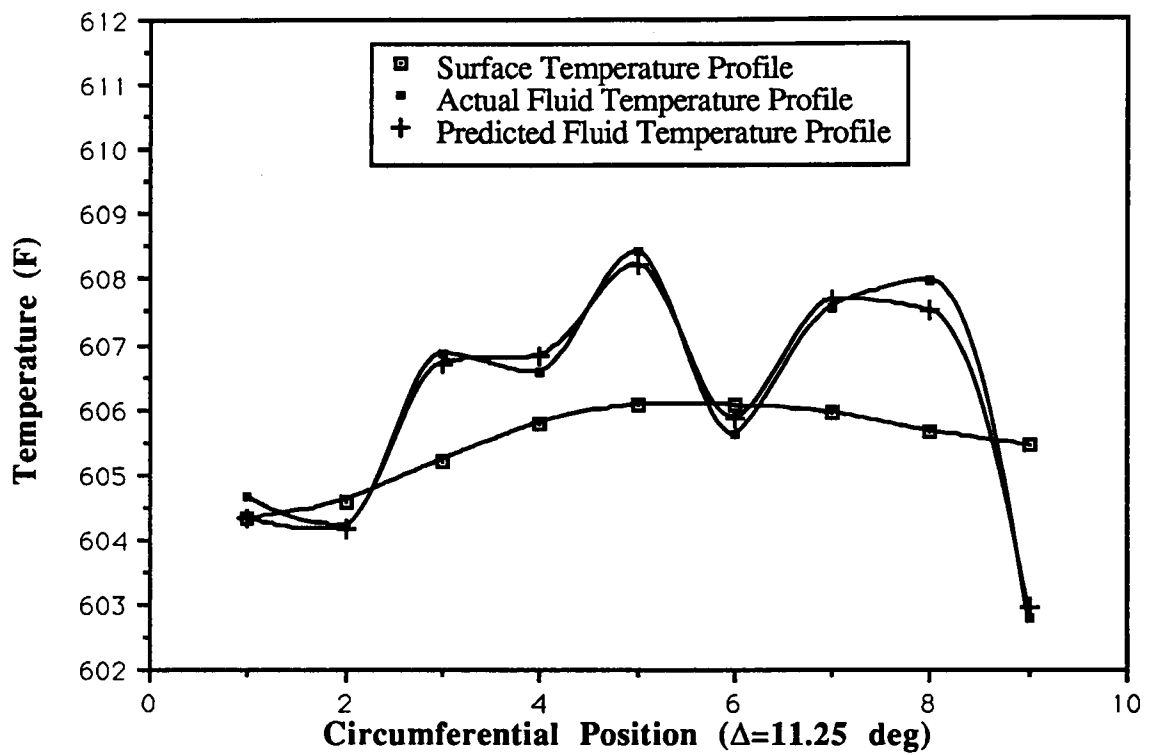


Figure 5.3 Fluid Temperature Profile Prediction Using Random Profile #12

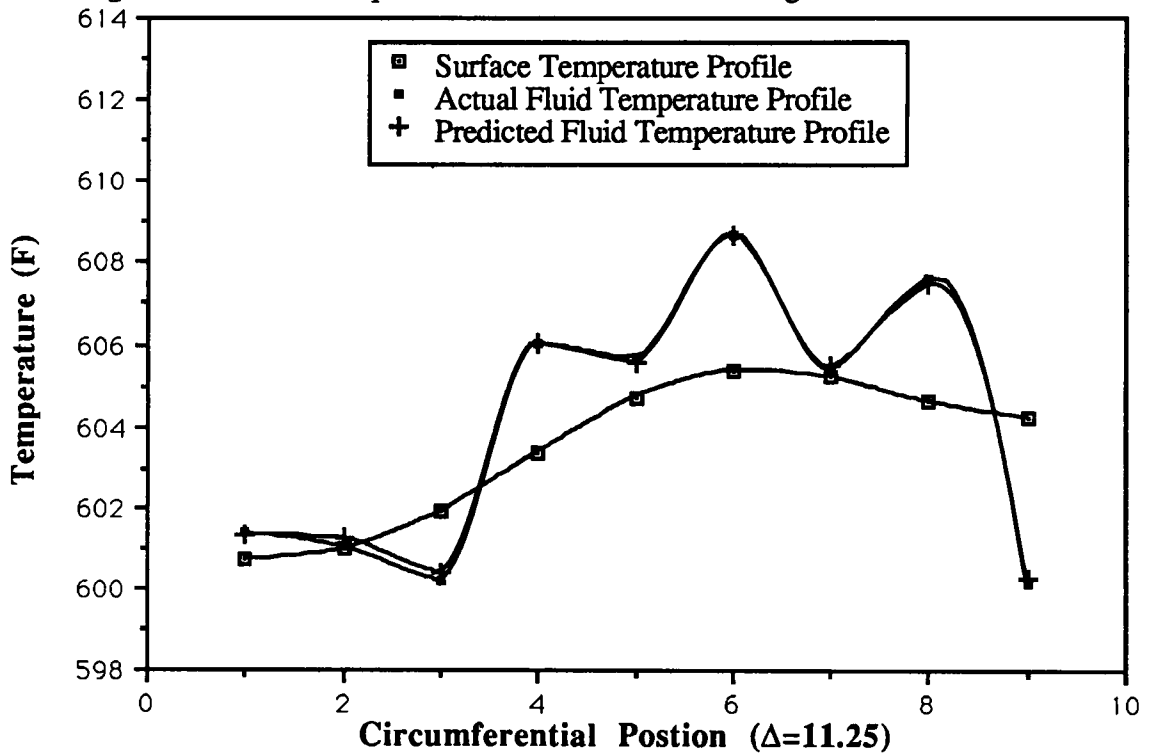


Figure 5.4 Fluid Temperature Profile Prediction Using Random Profile #13

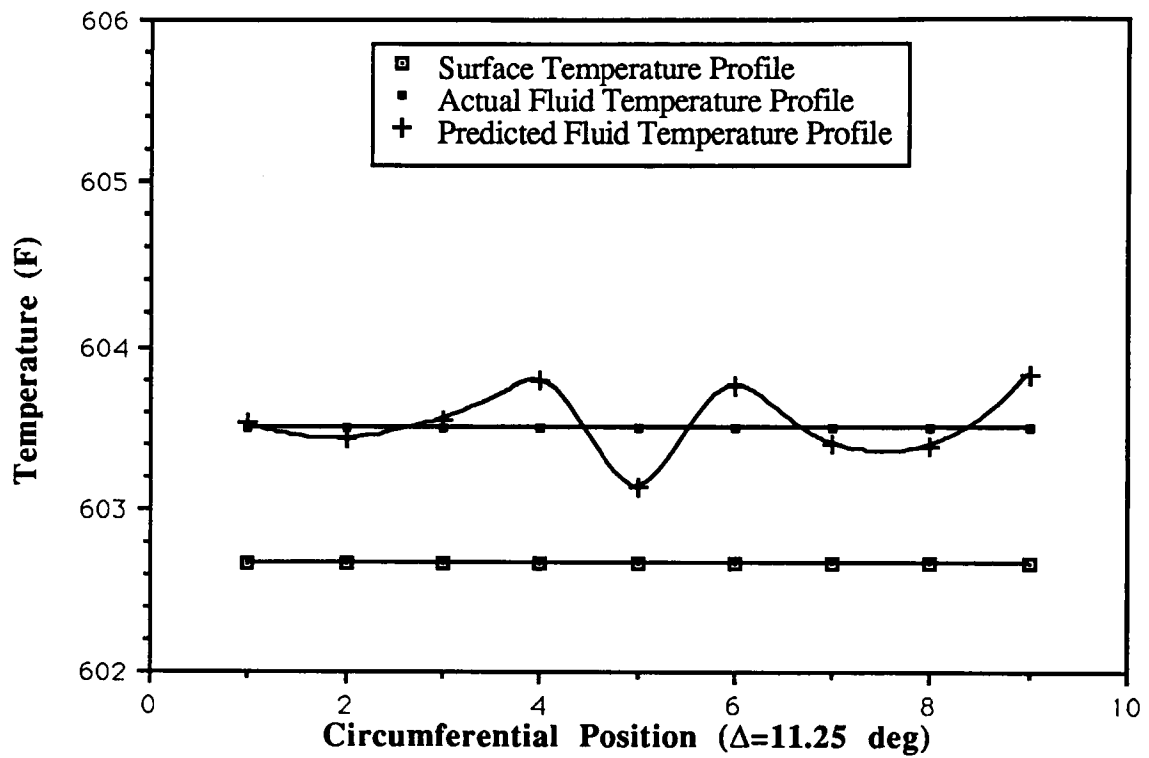


Figure 5.5 Fluid Temperature Profile Prediction Using Prescribed Profile #3

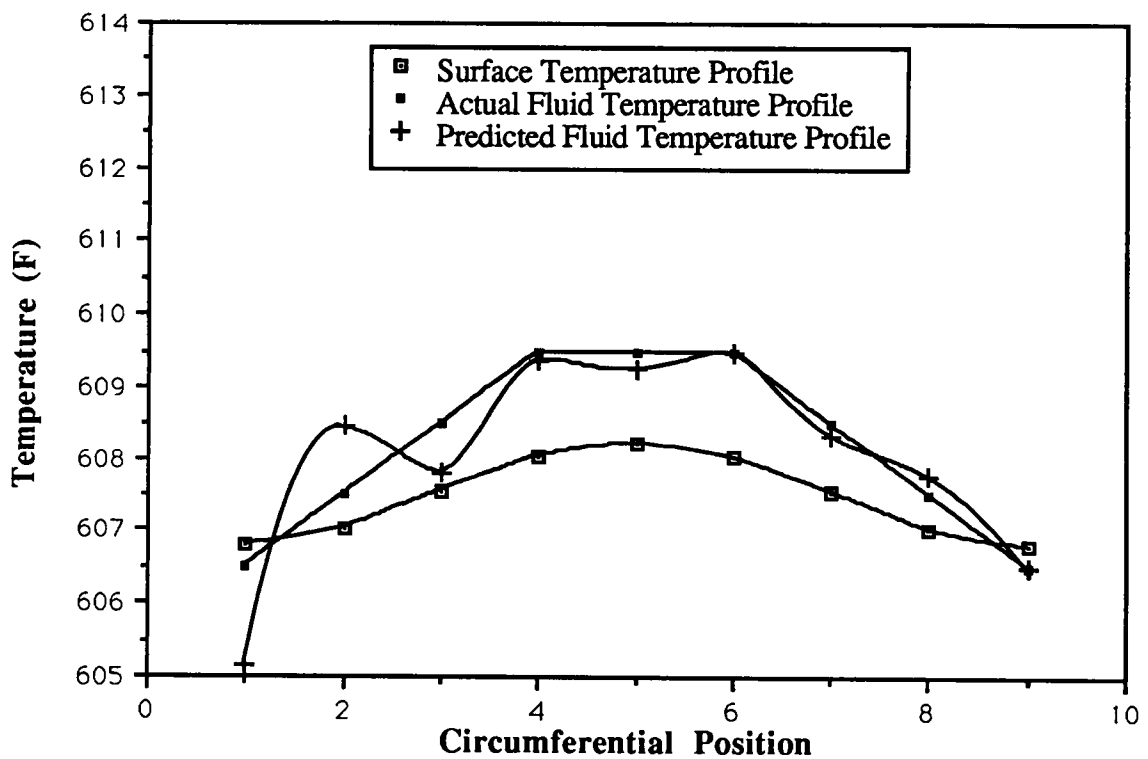


Figure 5.6 Fluid Temperature Profile Prediction Using Prescribed Profile #4

Chapter 6

HOT-LEG TEMPERATURE SENSITIVITY TO CORE EXIT TEMPERATURES

Introduction

The stratification in some PWR piping systems is considered to be the result of using the low neutron leakage fuel arrangement [2]. This fuel arrangement produces large temperature gradients in the outer regions of the core exit flow. The combination of large temperature gradients and limited fluid mixing is thought to cause the error in the computed bulk fluid temperature in the RCS.

These suspicions are investigated by studying the relationship between the core exit fluid temperature and the fluid temperature measured in the hot-legs. The analysis uses the associative ability of the neural network paradigm, backpropagation (BPN) to develop a functional relationship between the temperatures measured in core exit flow and in the hot-legs. Two networks are developed to perform the function mappings. One network is trained using core exit temperatures as inputs and measured hot-leg temperatures as the desired outputs, and one neural network is trained using the measured hot-leg temperatures as the inputs and the core exit temperatures as the desired outputs.

Once the training is complete, the mathematical structure of the BPN is analyzed [16]. The outcome of this analysis indicates the sensitivity of each measured hot-leg temperature to the core exit temperatures. The analysis was restricted by the availability of core exit and hot-leg temperature data: only one set of data was available. Therefore, the results presented are not conclusive but are intended to illustrate the benefits of this procedure when more data becomes available.

Core Exit and Hot-Leg Temperature Data

The data used in the study is from a 4 loop PWR. It includes core exit thermocouple measurements and corresponding hot-leg RTD measurements using the low neutron leakage fuel arrangement and one set of core exit temperature measurements using a uniform fuel arrangement.

The core exit temperatures of the two fuel arrangements have distinctive characteristics. Figures 6.1 and 6.2 illustrate the radial core exit temperatures using the uniform and low neutron leakage fuel arrangement, respectively. These figures also present a polynomial least squares approximation of the radial temperature distribution. From Figure 5.1 the temperature distribution across the core is relatively uniform considering the results of the polynomial approximation. Figure 6.2 illustrates the large temperature gradient in the outer regions of the core that are suspect in hot-leg stratification of the low neutron leakage fuel arrangement. The actual core exit thermocouple measurements are listed in Appendix A.

The hot-leg fluid temperature of each loop is measured using 3 RTDs. The RTDs are mounted in thermowells that are equally spaced around the circumference of the pipe (see Figure 6.3). For convenience, the RTDs will be referenced according to their position in each loop (i.e., T1 (top), T2 (left), and T3 (right)). The RTD measurements are listed in Table 6.1.

Sensitivity Study Using Neural Networks

The neural network paradigm, Backpropagation, is known for its ability to perform complex functional mappings. The network maps an input vector X in n dimensional space to an output vector Y in m dimensional space. The functional form of this mapping is

$$Y = f(X) \quad (6.1)$$

where $Y = (y_1, y_2, \dots, y_m)$ and $X = (x_1, x_2, \dots, x_n)$.

The sensitivity of the output, Y , to changes in the input, X , can be computed by taking the partial derivative of equation 6.1. The partial derivative $\partial y_k / \partial x_i$ defines the rate of change between the components of the input and a component of the output. In other words, the greater the absolute value of $\partial y_k / \partial x_i$, the more sensitive y_k is to x_i . The derivative between the input and output vectors of a trained neural network can be derived from its mathematical structure.

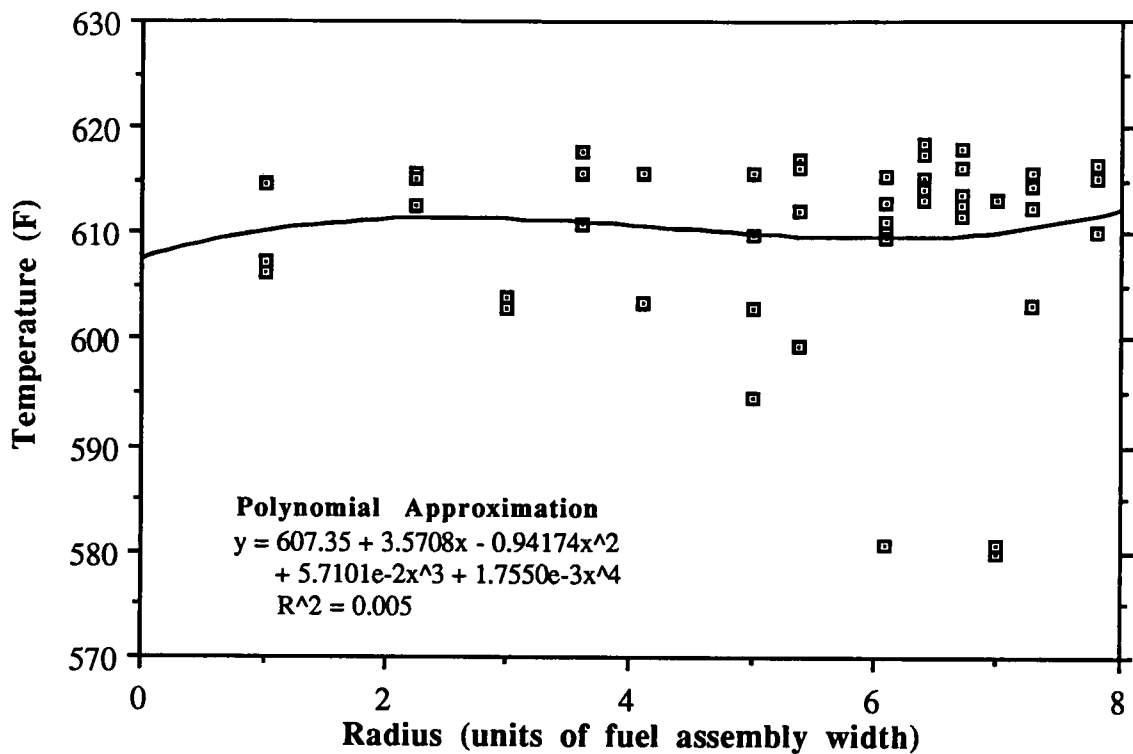


Figure 6.1 Radial Core Exit Temperature Profile Using Uniform Fuel Arrangement

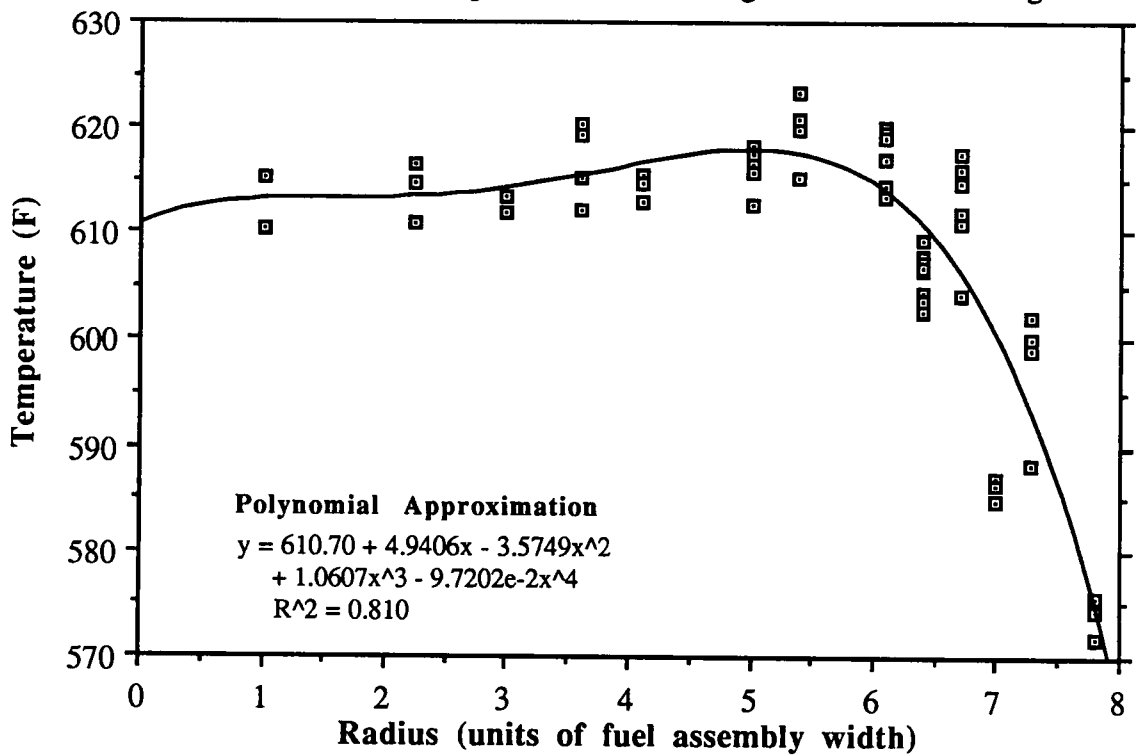


Figure 6.2 Radial Core Exit Temperature Profile Using Low Neutron Leakage Fuel Arrangement

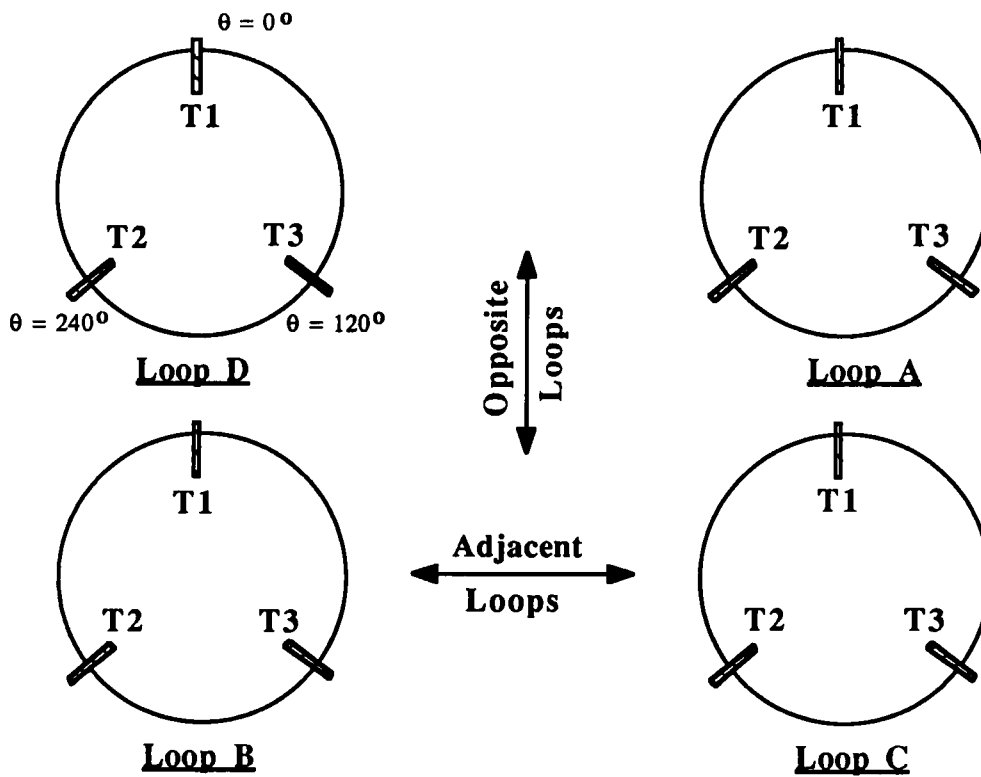


Figure 6.3 Hot-leg Loop and RTD Orientation

Table 6.1 Hot-leg RTD Measurements

Hot-Leg Loop	T1 (F)	T2 (F)	T3 (F)
A	609.6	608.0	610.9
B	612.2	610.0	604.8
C	609.8	610.9	607.6
D	608.9	611.0	604.6

The structure of the backpropagation network is shown in Figure 6.4, where w_{ij} is the weight connection between the i th and j th neuron, v_{jk} is the weighted connection between the j th and k th neurons, x_i is the input vector, z_j is the output of the j th neuron, and y_k is the output of the k th neuron.

The process of mapping X to Y can be expressed as

$$z_j = f(\sum_i w_{ij}x_i + \theta_j) \quad (6.2)$$

and

$$y_k = f(\sum_j v_{jk}z_j + \beta_k) \quad (6.3)$$

where θ_j is the threshold of the j th neuron, β_k is the threshold values of the k th neuron in the output layer, and $f()$ is the sigmoid transfer function. The sigmoid has the form

$$f(z) = 1 / (1 + e^{-\lambda z}) \quad (6.4)$$

where λ is the sigmoid slope. The derivative of the transfer function is

$$df(z)/dz = \lambda f(z)(1 - f(z)). \quad (6.5)$$

It follows that

$$\partial y_k / \partial x_i = \lambda y_k (1 - y_k) \sum_j v_{jk} \partial z_j / \partial x_i \quad (6.6)$$

where

$$\partial z_j / \partial x_i = \lambda z_j (1 - z_j) w_{ij}. \quad (6.7)$$

Substituting equation 6.7 into 6.6 yields

$$\partial y_k / \partial x_i = \lambda^2 y_k (1 - y_k) \sum_j v_{jk} z_j (1 - z_j) w_{ij}. \quad (6.8)$$

Equation 6.8 show that the sensitivity not only depends on the connection weights but also on the outputs of the j th and k th neurons. Therefore, $\partial y_k / \partial x_i$ may change as different input vectors are introduced. Since training and recall data may contain numerous patterns, summing the values of the partial derivative over all of the patterns will indicate the average sensitivity.

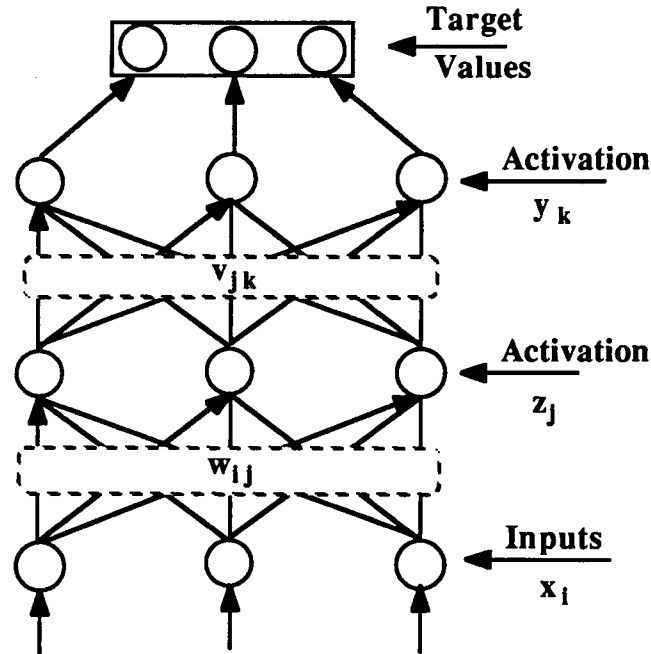


Figure 6.4 Backpropagation Network Structure

Developing Training Sets

The training set is comprised of the RTD measurement listed in Table 6.1 and the core exit temperature. The core exit temperature measurements are grouped into three regions, and the average temperature of each region is used for training. The fuel assembly grid of the core consists of 193 cells. Dividing these cells into three groups resulted in approximately 64 cells in each region. The three regions of the core are center, middle, and outer as shown in Figure 5.5. The average temperature for each region is listed in Table 5.2.

Sensitivity Results and Conclusions

The sensitivity analysis was conducted using 5 trained neural networks. Four of the networks were trained using the RTD measurements of each loop as the desired output and one neural network with the core exit temperatures as the desired output. The networks were developed using three input processing elements, PEs, three hidden layer PEs, and three output PEs. The trained networks were analyzed using a computer code written by Zhichao Guo [16].

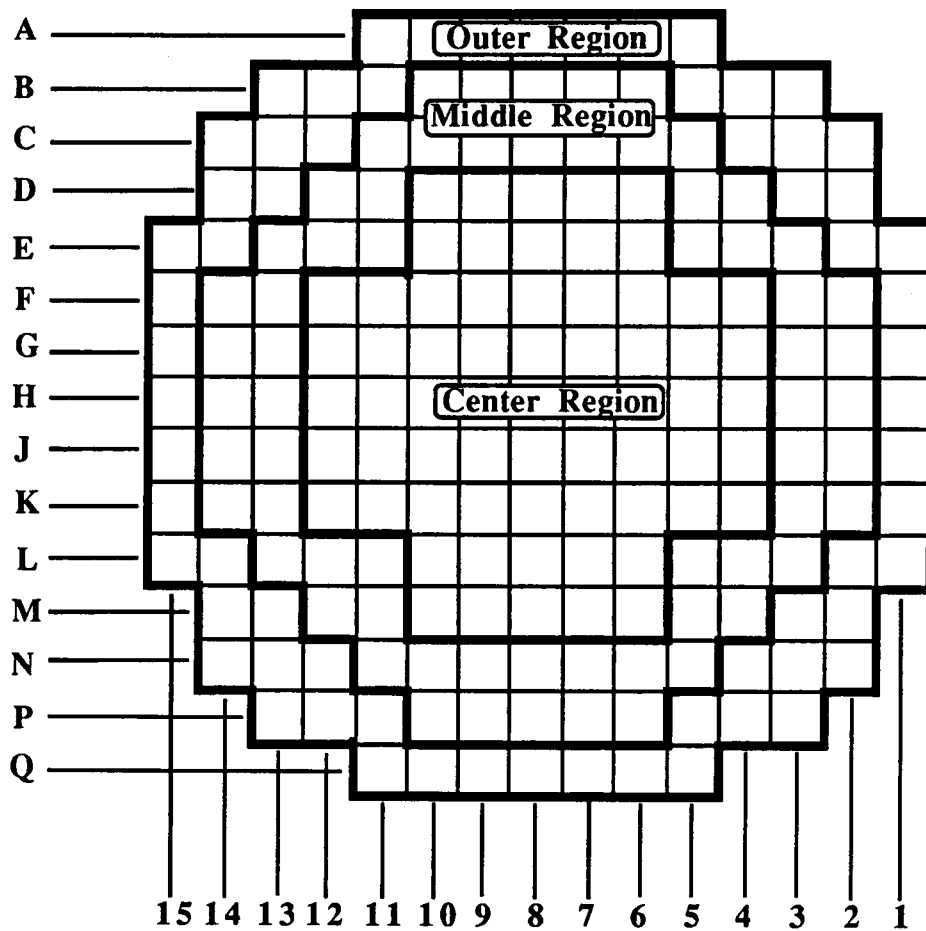


Figure 6.5 Core Exit Map of Regional Groups

Table 6.2 Regional Average Temperature of Core Exit Flow

Region	Temperature (F)
Center	614.56
Middle	613.73
Outer	587.27

Using Hot-Leg Temperatures as Desired Outputs

Four networks were developed and analyzed using the hot-leg RTD measurements as the desired outputs, and the results are listed in Tables 6.3-6.6. These tables contain the absolute values of the partial derivatives. The results show that the center region has the most influence on the fluid temperature in the hot-legs. The outer region also has a strong influence, and the middle region has the least influence.

Using Core Exit Temperatures as Desired Outputs

One neural network was trained using the hot-leg RTD measurements as inputs. The sensitivity analysis was performed, and the results are shown in Table 6.7. The results are listed in descending order of importance. These results show that the sensitivity of the output variables are ranked T2, T3, and T1, and that the center region has the most influence on the fluid temperature. These results compare with the previous model and thus substantiate the confidence in the results.

Table 6.3 Sensitivity Results Using Hot-leg Loop A RTD Measurements as Inputs

$\partial T1/\partial(\text{center})$	$\partial T1/\partial(\text{middle})$	$\partial T1/\partial(\text{outer})$
0.000020	0.000009	0.000015
$\partial T2/\partial(\text{center})$	$\partial T2/\partial(\text{middle})$	$\partial T2/\partial(\text{outer})$
0.000020	0.000009	0.000015
$\partial T3/\partial(\text{center})$	$\partial T3/\partial(\text{middle})$	$\partial T3/\partial(\text{outer})$
0.000020	0.000008	0.000015

Table 6.4 Sensitivity Results Using Hot-leg Loop B RTD Measurements as Inputs

$\partial T1/\partial(\text{center})$	$\partial T1/\partial(\text{middle})$	$\partial T1/\partial(\text{outer})$
0.000021	0.000010	0.000016
$\partial T2/\partial(\text{center})$	$\partial T2/\partial(\text{middle})$	$\partial T2/\partial(\text{outer})$
0.000021	0.000010	0.000016
$\partial T3/\partial(\text{center})$	$\partial T3/\partial(\text{middle})$	$\partial T3/\partial(\text{outer})$
0.000021	0.000009	0.000016

Table 6.5 Sensitivity Results Using Hot-leg Loop C RTD Measurements as Inputs

$\partial T1/\partial(\text{center})$	$\partial T1/\partial(\text{middle})$	$\partial T1/\partial(\text{outer})$
0.000021	0.000010	0.000016
$\partial T2/\partial(\text{center})$	$\partial T2/\partial(\text{middle})$	$\partial T2/\partial(\text{outer})$
0.000021	0.000010	0.000016
$\partial T3/\partial(\text{center})$	$\partial T3/\partial(\text{middle})$	$\partial T3/\partial(\text{outer})$
0.000021	0.000009	0.000016

Table 6.6 Sensitivity Results Using Hot-leg Loop D RTD Measurements as Inputs

$\partial T1/\partial(\text{center})$	$\partial T1/\partial(\text{middle})$	$\partial T1/\partial(\text{outer})$
0.000021	0.000010	0.000016
$\partial T2/\partial(\text{center})$	$\partial T2/\partial(\text{middle})$	$\partial T2/\partial(\text{outer})$
0.000021	0.000010	0.000016
$\partial T3/\partial(\text{center})$	$\partial T3/\partial(\text{middle})$	$\partial T3/\partial(\text{outer})$
0.000021	0.000009	0.000016

Table 6.7 Sensitivity Analysis using Core Exit Measurements as Inputs

Hot-Leg RTD	$\partial(\text{region})/\partial T_i$
Center Region	
T2	0.000480
T3	0.000389
T1	0.000311
Middle Region	
T2	0.000552
T3	0.000489
T1	0.000371
Outer Region	
T2	0.000661
T3	0.000573
T1	0.000421

Chapter 7

CONCLUSIONS

Experimental Conclusions

The results of the stratified flow experiments conclude that it is possible to estimate the bulk temperature of a fluid from measurements of the surface temperature of the pipe. Three methods of generating axial temperature profiles were evaluated: position profiles, ordered profiles, and average profiles. The results show that the average profile method produces the most accurate estimates of the bulk fluid temperature. The average absolute error was 0.15°F (0.13%). The results also show that the maximum estimation error is 0.30°F for all of the profile methods. The magnitude of average errors is similar for the three profile techniques, but the average profile method was consistently more accurate. Therefore, the average profile method is considered to be the superior method.

From an analysis performed using PWR data, the error in the bulk fluid temperature estimate using the three hot-leg RTDs is approximately 2.1°F where the average hot-leg temperature is approximately 610°F [4]. This results in an error of 0.34%. Comparing the error using the RTD measurements (0.34%) with the the average profile error of 0.13% indicates a potential reduction in the estimation error. Therefore, based on the experimental errors of the average profile method, the estimating process may increase the accuracy of the bulk temperature estimate. However, these experiments should not be used for extrapolating the temperature error of this method if applied to PWRs.

The results also show that the axial pipe surface temperatures approach an equilibrium temperature as the flow progresses along the pipe as expected. This convergence of the pipe surface temperature is the result of diffusion and fluid mixing. As the fluid mixes along the pipe, the fluid temperature also approaches an equilibrium temperature, and this is reflected in the surface temperature measurements.

From the sensitivity analysis, it is concluded that using more sensors at each axial position decreases the estimation error. The results also indicate that the number and location of temperature sensors may be determined experimentally. This process involves estimating the bulk temperature using more sensors in each estimate until the deviations in the estimate approach an asymptotic value, and the estimate of the bulk temperature remains consistent.

Conclusions of Furthering the Estimating Process

One of the errors involved in the estimation process is due to circumferential variations in the temperature difference between the pipe surface and the radial adjacent fluid. Therefore, finite element analysis and neural networks were used to process measured surface temperatures into discrete fluid temperatures. This process was capable of predicting fluid temperature with an average error of 0.06°F (0.01%). The maximum error computed for all of the recall data was 1.75°F (0.29%), and the average maximum error was 0.90°F (0.14%). These results show that this process will compute fluid temperatures with moderate accuracy. The ability of this process to increase the accuracy of the bulk temperature estimate was not evaluated experimentally, but the results look promising.

Conclusions of Hot-leg Sensitivity to Core Exit Temperatures

The sensitivity analysis performed using core exit and hot-leg temperature measurements indicate that the hot-leg RTD measurements have different relationships with the temperature of the core exit flow. The analysis procedure used average core exit temperatures from three regions of the core to study this relationship. The regions are the center, middle and outer ranges of the core, and the average temperatures are 614.56°F , 613.73°F , and 587.27°F , respectively. The results show that the individual RTD measurements, namely T1, T2, and T3, are most sensitive to the center region of the core exit. The core exit regions are ranked in order of importance as center, outer, and middle. The higher ratings of the center and outer regions indicate that the RTD measurements are most sensitive to the highest and lowest temperatures of the core exit flow. This suggested that the fluid may not be well mixed when the fluid temperature is measured by the RTDs.

A second analysis was performed. This analysis interchanged the inputs and outputs during training. The order of importance between the variables remained the same. The analysis performed in this study was restricted to only one set of training data.

Therefore, the results presented are not conclusive but are intended to illustrate the benefits of this procedure if more information becomes available.

Chapter 8

FUTURE WORK

Automated Estimating System

The results of this work show that surface temperature measurements can be processed into estimates of the bulk fluid temperature. The process of estimating the bulk temperature requires manually recording and processing of much of the surface temperature data. An automated system could be developed. The system could collect and validate the surface temperature measurements, compensate for faulty measurements, and compute the estimated bulk fluid temperature. From a developmental point of view, the benefits of an automated estimating system are that the amount of time bulk temperature estimates can be reduced, and the effects of bulk temperature transients can be studied.

Future Work for Furthering the Estimating Process

A method for improving the accuracy of the estimation process was proposed. The preliminary results look promising. Future work on the estimation process includes experimental verification. The success of training a neural network to predict fluid temperatures for pipe surface temperatures indicate that neural networks may be used to predict the bulk temperature of a fluid from surface temperature measurements made at a single cross section of a pipe. One primary concern would be obtaining reliable training data.

Future Work of Hot-leg Sensitivity to Core Exit Temperatures

Using one set of core exit temperatures and RTD measurements, the results of the sensitivity analysis show that the RTDs measurements are influenced differently by different regions of the core exit flow. The credibility of the analysis increases as the number of training data increases.

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APPENDICES

Appendix A

CORE EXIT AND HOT-LEG TEMPERATURE DATA

The temperature measurements presented below are from a 4-loop PWR. Table A.1 and A.2 are core exit thermocouple measurements made during two different fuel cycles, and Table A.3 is corresponding hot-leg RTD measurements.

Table A.1 Core Exit Thermocouple, TC, Data For Cycle 4

TC Location	Radius* (FAW)	Temperature (F)	TC Location	Radius (FAW)	Temperature (F)
H07	1.00	607.3	J14	6.08	612.9
G08	1.00	614.8	P07	6.08	580.6
J08	1.00	606.3	P09	6.08	
F09	2.24	615.8	C04	6.40	618.4
J06	2.24	615.2	C12	6.40	613.1
J10			D03	6.40	615.1
K09	2.24	612.7	D13	6.40	
H11	3.00	603.0	M03	6.40	617.4
L08	3.00	604.0	M13	6.40	614.5
E06	3.60		N04	6.40	614.2
E10	3.60	617.8	N12	6.40	
F05	3.60	610.8	B05	6.71	
K05	3.60	615.7	B11	6.71	616.1
D07	4.12		E02	6.71	612.6
G04	4.12	615.7	E14	6.71	
G12	4.12		L02	6.71	613.6
M07	4.12	603.4	L14	6.71	618.0
C08	5.00	603.0	P05	6.71	611.7
D11	5.00	615.8	H01	7.00	579.9
H03	5.00		H15	7.00	560.7
L04	5.00	594.4	R08	7.00	613.2
L12	5.00	609.9	A06	7.28	603.1
M11	5.00		F01	7.28	612.5
C06	5.38	616.9	F15	7.28	615.6

*Radius of Fuel Assembly Width

Table A.1 (Cont.)

TC Location	Radius (FAW)	Temperature (F)	TC Location	Radius (FAW)	Temperature (F)
F13	5.38	617.1	K01	7.28	614.7
K13	5.38	616.3	K15	7.28	614.4
N06	5.38	599.3	R10	7.28	
N10	5.38	612.1	B03	7.81	615.1
B09	6.08	610.7	B13	7.81	610.2
G02	6.08	609.5	N02	7.81	616.4
G14	6.08	615.4	N14	7.81	
J02	6.08	611.1			

Table A.2 Core Exit Thermocouple, TC, Data For Cycle 5

TC Location	Radius (FAW)	Temperature (F)	TC Location	Radius (FAW)	Temperature (F)
H07	1.00	615.2	J14	6.08	617.1
G08	1.00		P07	6.08	617.1
J08	1.00	610.4	P09	6.08	619.0
F09	2.24	614.7	C04	6.40	607.7
J06	2.24		C12	6.40	607.2
J10		610.9	D03	6.40	606.6
K09	2.24	616.4	D13	6.40	602.6
H11	3.00	613.4	M03	6.40	606.7
L08	3.00	611.9	M13	6.40	604.5
E06	3.60	612.2	N04	6.40	603.7
E10	3.60	615.2	N12	6.40	609.2
F05	3.60	620.4	B05	6.71	617.5
K05	3.60	619.4	B11	6.71	616.0
D07	4.12	615.4	E02	6.71	614.8
G04	4.12	614.8	E14	6.71	604.1
G12	4.12	612.9	L02	6.71	612.0
M07	4.12		L14	6.71	
C08	5.00	618.2	P05	6.71	610.9
D11	5.00	616.4	H01	7.00	587.2
H03	5.00	617.4	H15	7.00	586.4
L04	5.00	612.7	R08	7.00	584.7
L12	5.00	615.7	A06	7.28	599.1
M11	5.00		F01	7.28	
C06	5.38	620.1	F15	7.28	588.4
F13	5.38	615.3	K01	7.28	600.1
K13	5.38	623.4	K15	7.28	602.1
N06	5.38	620.7	R10	7.28	602.1
N10	5.38	619.8	B03	7.81	574.4
B09	6.08	620.1	B13	7.81	575.4
G02	6.08	619.5	N02	7.81	575.5
G14	6.08	614.3	N14	7.81	571.8
J02	6.08	613.5			

Table A.3 Hot-Leg RTD Temperature Data

Hot-Leg Loop No.	T1 (F)	T2 (F)	T3 (F)	Tave (F)	S1 (F)	S2 (F)	S3 (F)	SA1 (F)	SA2 (F)	SA3 (F)
	Instantaneous				Instantaneous			5 minute average		
	6/19/90									
A	609.6	611.0	607.8	609.5	0.1	1.5	-1.7	0.08	1.40	-1.48
B	611.5	605.8	609.8	609.0	2.5	-3.2	0.8	3.21	-4.18	0.98
C	609.9	607.3	611.1	609.4	0.5	-2.1	1.7	0.36	-1.81	1.45
D	608.8	604.6	611.1	608.2	0.6	-3.6	2.9	0.68	-3.51	2.82
	6/22/90									
A	609.7	611.3	608.7	609.9	-0.2	1.4	-1.2	0.09	1.35	2.76
B	612.3	605.9	610.6	609.6	2.7	-3.7	1.0	3.22	-4.19	-1.44
C	609.9	608.2	611.5	609.9	0.0	-1.7	1.6	0.48	-1.94	0.97
D	610.7	605.0	611.9	609.2	1.5	-4.2	2.7	0.79	-3.55	2.76
	6/26/90									
A	609.3	611.2	608.2	609.6	-0.3	1.6	-1.4	0.04	1.52	-1.57
B	612.6	604.9	610.1	609.2	3.4	-4.3	0.9	3.20	-4.17	0.97
C	609.7	608.4	610.9	609.7	0.0	-1.3	1.2	0.37	-1.80	1.43
D	609.2	604.9	611.4	608.5	0.7	-3.6	2.9	0.74	-3.50	2.76
	6/27/90									
A	610.0	611.6	607.8	609.8	0.2	1.8	-2.0	0.09	1.41	-1.50
B	612.5	605.1	610.3	609.3	3.2	-4.2	1.0	3.16	-4.10	0.94
C	610.2	607.6	610.9	609.6	0.6	-2.0	1.3	0.35	-1.76	1.41
D	609.5	604.9	611.3	608.6	0.9	-3.7	2.7	0.66	-3.36	2.70
	7/02/90									
A	609.3	610.7	607.4	609.1	0.2	1.6	-1.7		same	
B	612.0	603.9	609.5	608.5	3.5	-4.6	1.0	3.19	-4.18	0.95
C	609.3	607.5	609.9	608.9	0.4	-1.4	1.0	0.34	-1.70	1.36
D	607.9	604.3	609.6	607.3	0.6	-3.0	2.3	0.66	-3.37	2.71
	7/05/90									
A	609.3	611.0	608.7	609.7	-0.4	1.3	-1.0		same	
B	612.3	604.9	609.8	609.0	3.3	-4.1	0.8	3.17	-4.15	0.98
C	609.5	606.4	610.6	608.8	0.7	-2.4	1.8	0.31	-1.68	1.37
D	608.3	604.5	610.8	607.9	0.4	-3.4	2.9	0.66	-3.35	2.68
	7/10/90									
A	609.4	610.7	608.5	609.5	-0.1	1.2	-1.0		same	
B	612.1	604.6	610.2	609.0	3.1	-4.4	1.2	3.19	-4.11	0.92
C	609.4	606.9	610.3	608.9	0.5	-2.0	1.4	0.36	-1.75	1.37
D	608.4	604.8	610.0	607.7	0.7	-2.9	2.3	0.64	-3.28	2.65
	7/13/90									
A	609.4	611.0	607.6	609.3	0.1	1.7	-1.7		same	
B	612.0	605.4	609.9	609.1	2.9	-3.7	0.8	3.15	-4.06	0.91
C	609.5	608.1	610.4	609.3	0.2	-1.2	1.1	0.37	-1.76	1.38
D	609.1	605.2	611.0	608.4	0.7	-3.2	2.6	0.70	-3.34	2.64

Appendix B

EXPERIMENTAL FACILITY EQUIPMENT LIST

The following is a list of the components used to construct the experimental apparatus.

1. 2105a Multipoint Switch Unit
2. 2100A Digital Thermometer
3. 50 feet of 24 guage, K type thermocouple wire
4. Thermocouple welder
5. 6 feet of 1" diameter, schedule 40, threaded water pipe
6. Two 1" dia. threaded elbow
7. Four 1" diameter, 'Y' fitting with valves
8. Aluminum plate for constructing flow dividers
9. 6 feet of 3/4" pipe insulation
10. One collecting reservoir, 3 gallon capacity
11. Two 3/4" rubber hoses
12. Water heater, 50 gallon capacity
13. Assortment of vanes to induce various flow patterns

Appendix C

EXPERIMENTAL PARAMETERS AND SURFACE TEMPERATURE MEASUREMENTS

The measurements made during the stratified flow experiments are presented in the following tables. Table C.1 contains the inlet hot and cold water temperatures and the bulk fluid temperature measured during each experiment. The surface temperature measurements are presented in table C.2.

Table C.1 Inlet Hot and Cold Water Temperatures and the Measured Bulk Fluid Temperature, T_{mb} , of Stratified Flow Experiments

Experiment No.	T_{hot} (°F)	T_{cold} (°F)	T_{mb} (°F)
1	131.2	74.0	105.6
2	136.4	73.0	107.3
3	133.2	90.0	107.0
4	138.5	70.0	116.3
5	133.9	70.0	91.5
6	153.9	81.0	119.6
7	153.8	99.0	125.3
8	149.0	83.0	99.8
9	146.5	80.0	109.1
10	146.6	80.0	109.2
11	143.9	85.0	109.3
12	143.0	80.0	108.7
13	148.0	118.0	127.3
14	148.0	115.0	125.3
15	150.0	111.0	128.0
16	154.0	110.0	128.7
17	155.0	111.0	128.6
18	155.0	110.0	128.7

Table C.1 (Cont.)

19	151.7	93.0	108.5
20	151.5	92.0	107.6
21	151.0	80.0	99.6
22	132.0	81.0	100.9
23	131.0	81.6	106.3
24	131.0	83.2	120.7
25	152.0	119.0	126.2
26	153.2	104.0	125.7
27	153.1	103.0	126.2
28	153.1	103.0	126.2
29	155.0	80.0	103.5
30	150.0	85.0	122.5
31	153.1	104.0	125.8

Table C.2 Surface Temperature Measurements Recorded During 31 Stratified Flow Experiments.

Experiment #1					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	106.40	97.00	98.00	114.30	103.93
14	108.10	102.50	100.20	107.60	104.60
20	107.60	104.50	102.00	104.40	104.63
26	107.30	105.30	103.20	104.20	105.00
32	106.60	105.60	103.90	104.40	105.13
38	106.40	105.70	104.50	104.80	105.35
44	106.40	105.60	104.70	105.10	105.45
Experiment #2					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	108.60	98.80	99.20	117.00	105.90
14	110.60	104.80	101.70	110.00	106.78
20	109.80	106.50	103.70	106.30	106.58
26	109.30	107.00	105.10	106.20	106.90
32	108.20	107.40	105.60	106.40	106.90
38	108.00	107.50	106.20	106.80	107.13
44	107.80	107.60	106.50	106.90	107.20
Experiment #3					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	109.00	108.00	104.90	103.90	106.45
14	106.60	107.90	107.00	106.50	107.00
20	107.40	107.10	106.70	106.50	106.93
26	107.40	107.00	107.00	106.50	106.98
32	107.20	106.89	106.70	106.80	106.90
38	107.20	107.00	106.80	106.80	106.95
44	107.10	107.00	107.00	106.80	106.98
Experiment #4					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	119.70	112.40	112.00	121.60	116.43
14	119.30	115.80	113.20	118.20	116.63
20	118.40	116.00	113.90	116.20	116.13
26	118.00	116.10	114.90	115.80	116.20
32	116.90	116.50	115.00	115.60	116.00
38	116.90	116.50	115.50	115.80	116.18
44	117.10	116.50	115.70	115.80	116.28

Table C.2 (Cont.)

Experiment #5					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	93.70	91.50	89.40	89.60	91.05
14	92.00	92.20	91.30	90.80	91.58
20	91.50	91.70	91.60	91.20	91.50
26	91.40	91.70	91.70	91.30	91.53
32	91.60	91.40	91.50	91.40	91.48
38	91.50	91.40	91.50	91.40	91.45
44	91.50	91.40	91.50	91.40	91.45
Experiment #6					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	124.50	116.50	115.20	123.90	120.0
14	122.10	120.30	116.80	120.50	119.9
20	122.00	120.30	117.20	118.70	119.6
26	121.40	120.40	118.30	118.40	119.6
32	119.80	120.40	118.40	118.70	119.3
38	119.90	120.60	119.00	118.90	119.6
44	119.90	120.20	119.10	119.20	119.6
Experiment #7					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	123.4	124.5	125.6	124.8	124.7
14	124.5	125.0	125.0	125.1	124.8
20	124.5	125.1	124.0	125.2	124.8
26	124.8	124.8	124.5	125.2	124.9
32	124.5	124.9	125.0	125.5	125.0
38	124.7	125.0	125.0	125.4	125.0
44	124.8	125.1	125.2	125.0	125.0
Experiment #8					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	100.6	99.0	99.6	100.8	100.0
14	100.5	99.5	99.6	100.0	99.9
20	100.3	99.6	99.3	99.9	99.8
26	100.0	99.6	99.6	99.6	99.7
32	99.5	99.6	99.5	99.7	99.6
38	99.9	99.7	99.6	99.6	99.7
44	99.9	99.4	99.5	99.2	99.5

Table C.2 (Cont.)

Experiment #9					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	109.00	106.50	107.00	106.10	107.2
14	107.20	106.90	109.60	109.10	108.2
20	108.70	109.00	108.70	108.00	108.6
26	109.00	108.50	108.50	109.00	108.8
32	108.00	108.40	108.90	109.10	108.6
38	108.50	108.80	109.10	109.10	108.9
44	108.70	108.90	109.10	109.00	108.9
Experiment #10					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	109.00	106.90	106.60	106.40	107.23
14	107.50	107.40	109.90	109.20	108.50
20	108.90	109.60	108.80	108.10	108.85
26	109.20	109.00	108.70	109.20	109.03
32	108.20	108.80	109.00	109.30	108.83
38	108.40	109.00	109.00	109.10	108.88
44	108.70	109.00	109.00	108.90	108.90
Experiment #11					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	108.50	109.30	106.00	108.30	108.03
14	107.60	104.90	109.90	108.70	107.78
20	110.00	109.30	108.30	108.60	109.05
26	109.40	108.70	109.20	109.60	109.23
32	108.30	109.20	109.30	109.30	109.03
38	109.00	109.30	109.30	109.20	109.20
44	109.30	109.10	109.30	109.20	109.23
Experiment #12					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	109.10	108.80	108.60	107.10	108.40
14	108.20	104.90	103.40	107.90	106.10
20	107.10	108.90	109.20	107.70	108.23
26	109.30	108.80	107.70	108.60	108.60
32	109.00	108.80	108.40	108.30	108.63
38	107.90	108.50	108.70	108.20	108.33
44	108.50	108.70	108.50	108.00	108.43

Table C.2 (Cont.)

Experiment #13					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	127.30	125.90	126.70	127.40	126.83
14	127.30	126.70	126.80	127.00	126.95
20	126.90	127.10	126.90	127.10	127.00
26	127.20	126.90	127.00	126.90	127.00
32	127.00	127.10	126.80	127.00	126.98
38	126.90	127.10	127.10	127.00	127.03
44	127.10	127.10	127.10	126.80	127.03
Experiment #14					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	126.6	123.6	124.2	124.3	124.7
14	126.3	124.8	124.3	124.7	125.0
20	125.7	124.9	123.9	124.8	124.8
26	125.9	124.8	124.6	124.5	125.0
32	125.5	125.0	124.7	124.6	125.0
38	125.5	125.1	124.5	124.6	124.9
44	125.6	125.2	124.9	124.8	125.1
Experiment #15					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	127.5	128.0	128.3	128.8	128.2
14	128.1	128.1	128.2	128.2	128.2
20	127.7	128.0	127.6	128.3	127.9
26	127.9	127.7	128.3	128.0	128.0
32	127.6	127.8	128.0	128.1	128.0
38	127.8	127.9	128.2	128.3	128.0
44	127.8	127.7	128.0	127.7	127.7
Experiment #16					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	128.3	128.8	129.4	129.6	129.0
14	129.3	129.1	129.1	128.8	129.1
20	128.7	129.1	128.4	129.0	128.8
26	128.9	128.8	129.2	128.6	128.9
32	128.6	129.0	128.7	129.0	128.8
38	128.3	129.2	128.9	128.9	128.8
44	128.6	128.7	128.8	128.4	128.6

Table C.2 (Cont.)

Experiment #17					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	128.6	128.7	129.3	129.6	129.1
14	129.3	129.1	129.0	128.7	129.0
20	128.9	129.0	128.3	128.9	128.8
26	129.1	128.7	129.0	128.6	128.9
32	128.6	128.8	128.6	128.9	128.7
38	128.4	128.9	128.9	128.7	128.7
44	128.6	128.6	128.7	128.5	128.6
Experiment #18					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	128.5	128.6	129.1	129.3	128.9
14	129.3	128.8	128.8	128.6	128.9
20	128.6	128.9	128.7	128.7	128.7
26	128.8	128.6	128.7	128.4	128.6
32	128.6	128.6	128.6	128.7	128.6
38	128.3	128.7	128.8	128.5	128.6
44	128.4	128.7	128.6	128.5	128.6
Experiment #19					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	108.4	108.5	108.6	108.4	108.5
14	108.7	108.5	108.6	108.1	108.5
20	108.6	108.7	108.0	108.2	108.4
26	108.6	108.4	108.7	108.0	108.4
32	108.4	108.5	108.4	108.2	108.4
38	108.2	108.5	108.5	108.0	108.3
44	108.4	108.0	108.5	108.0	108.2
Experiment #20					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	107.6	107.4	107.6	107.5	107.5
14	108.0	107.7	107.5	107.3	107.6
20	107.7	107.7	107.2	107.5	107.5
26	107.7	107.6	107.7	107.3	107.6
32	107.6	107.7	107.4	107.4	107.5
38	107.5	107.6	107.6	107.4	107.5
44	107.7	107.4	107.5	107.3	107.5

Table C.2 (Cont.)

Experiment #21					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	99.70	99.40	99.40	99.50	99.5
14	99.90	99.70	99.40	99.20	99.6
20	99.70	99.60	99.20	99.30	99.5
26	99.70	99.60	99.60	99.30	99.6
32	99.60	99.60	99.50	99.30	99.5
38	99.60	99.50	99.60	99.40	99.5
44	99.60	99.40	99.50	99.20	99.4
Experiment #22					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	98.50	99.70	100.80	101.00	100.0
14	99.20	99.80	101.00	101.00	100.3
20	99.80	100.20	100.50	101.10	100.4
26	100.00	100.30	100.90	101.00	100.6
32	99.70	100.40	100.70	101.10	100.5
38	99.80	100.50	101.00	101.00	100.6
44	99.90	100.60	101.00	100.90	100.6
Experiment #23					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	106.20	106.20	105.90	106.00	106.1
14	106.40	106.20	106.30	106.20	106.3
20	106.30	106.40	106.10	106.20	106.3
26	106.50	106.20	106.20	106.10	106.3
32	106.10	106.20	106.10	106.30	106.2
38	106.10	106.20	106.20	106.20	106.2
44	106.20	106.10	106.20	106.10	106.2
Experiment #24					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	119.60	120.30	120.30	120.30	120.1
14	120.50	120.40	120.70	120.40	120.5
20	120.40	120.70	120.10	120.50	120.4
26	120.60	120.50	120.80	120.40	120.6
32	120.40	120.60	120.50	120.60	120.5
38	120.40	120.60	120.60	120.50	120.5
44	120.50	120.40	120.50	120.60	120.5

Table C.2 (Cont.)

Experiment #25					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	125.80	125.50	126.10	126.40	126.0
14	126.10	125.90	126.10	126.00	126.0
20	125.90	126.10	125.90	126.10	126.0
26	126.10	125.80	126.10	126.00	126.0
32	125.90	125.80	125.90	126.10	125.8
38	125.80	126.10	126.10	126.10	126.0
44	126.00	125.90	126.10	126.20	126.1
Experiment #26					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	125.00	125.50	125.60	125.30	125.4
14	125.70	125.60	125.50	125.30	125.5
20	125.60	125.70	125.60	125.50	125.6
26	125.60	125.40	125.50	125.50	125.5
32	125.70	125.60	125.40	125.60	125.6
38	125.50	125.60	125.60	125.60	125.6
44	125.50	125.60	125.50	125.60	125.6
Experiment #27					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	125.30	125.80	126.50	126.50	126.0
14	125.90	125.90	126.40	126.20	126.1
20	125.90	126.30	125.60	126.40	126.0
26	126.10	125.90	126.30	126.30	126.2
32	125.80	126.20	126.10	126.00	126.0
38	125.90	126.10	126.30	126.40	126.2
44	125.95	126.20	126.20	126.00	126.1
Experiment #28					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	125.7	125.8	126.5	125.7	125.9
14	126.1	126.1	126.2	125.8	126.0
20	126.0	126.0	125.8	125.9	125.9
26	126.1	125.9	126.1	125.8	126.0
32	125.9	126.1	126.2	126.0	126.1
38	125.8	126.1	126.0	125.9	125.9
44	126.0	126.2	126.1	126.1	126.1

Table C.2 (Cont.)

Experiment #29					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	103.3	103.3	103.5	103.9	103.5
14	103.8	104.3	103.5	103.2	103.7
20	103.6	104.1	102.9	103.2	103.4
26	104.0	103.5	103.4	102.9	103.5
32	103.8	103.5	103.2	103.0	103.4
38	103.6	103.5	103.5	103.0	103.4
44	103.6	102.8	103.1	103.2	103.2
Experiment #30					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	122.9	122.1	122.8	123.0	122.7
14	123.4	122.9	122.7	122.2	122.8
20	122.9	122.7	122.9	122.2	122.7
26	122.9	122.5	122.5	121.9	122.5
32	122.9	122.3	122.1	122.2	122.4
38	122.2	122.5	122.3	122.2	122.3
44	122.4	122.9	122.1	122.2	122.4
Experiment #31					
Axial Position (in)	Circumferential		Temperature		Position Average (F)
	(F)	(F)	(F)	(F)	
	$\theta = 0$	$\theta = 90$	$\theta = 180$	$\theta = 270$	
8	125.0	125.5	125.6	125.3	125.4
14	125.7	125.6	125.5	125.8	125.7
20	125.6	125.7	125.6	125.5	125.6
26	125.6	125.4	125.5	125.5	125.5
32	125.7	125.6	125.7	125.6	125.6
38	125.5	125.6	125.8	125.6	125.6
44	125.8	125.6	125.6	125.7	125.7

Table C.3 Average Absolute Error Using Position Profile Method and Four Circumferential Sensors at each Axial Position

Number of Axial Sensor Rings	Average Error	Maximum Error	Standard Deviation
7	0.16	0.28	0.06
6	0.27	1.20	0.22
5	0.20	0.74	0.17
4	0.26	0.73	0.21
3	0.38	0.96	0.30
2	0.57	2.22	0.55

Table C.4 Average Absolute Error Using Position Profile Method and Three Circumferential Sensors at each Axial Position ($\theta = 0$, $\theta = 180$, $\theta = 270$)

Number of Axial Sensor Rings	Average Error	Maximum Error	Standard Deviation
7	0.29	0.96	0.23
6	0.29	0.86	0.20
5	0.17	0.65	0.15
4	0.30	0.76	0.20
3	0.42	1.09	0.34
2	0.55	1.73	0.47

Table C.5 Average Absolute Error Using Position Profile Method and Two Circumferential Sensors at each Axial Position ($\theta = 0$, $\theta = 180$)

Number of Axial Sensor Rings	Average Error	Maximum Error	Standard Deviation
7	0.33	1.50	0.42
6	0.41	1.64	0.41
5	0.35	1.08	0.26
4	0.45	1.80	0.36
3	0.52	1.75	0.41
2	0.72	1.96	0.53

Table C.6 Average Absolute Error Using Ordered Profile Method and Four Circumferential Sensors at each Axial Position

Number of Axial Sensor Rings	Average Error	Maximum Error	Standard Deviation
7	0.16	0.28	0.08
6	0.27	1.21	0.23
5	0.20	0.74	0.17
4	0.27	0.73	0.19
3	0.39	0.96	0.29
2	0.57	1.73	0.49

Table C.7 Average Absolute Error Using Ordered Profile Method and Three Circumferential Sensors at each Axial Position

Number of Axial Sensor Rings	Average Error	Maximum Error	Standard Deviation
7	0.28	0.96	0.23
6	0.28	0.86	0.20
5	0.17	0.65	0.15
4	0.31	0.77	0.20
3	0.38	1.09	0.34
2	0.52	1.73	0.43

Table C.8 Average Absolute Error Using Ordered Profile Method and Two Circumferential Sensors at each Axial Position

Number of Axial Sensor Rings	Average Error	Maximum Error	Standard Deviation
7	0.21	1.12	0.25
6	0.30	1.44	0.29
5	0.21	1.08	0.24
4	0.38	1.00	0.26
3	0.45	1.40	0.39
2	0.54	1.55	0.41

Table C.9 Average Absolute Error Using Average Profile Method and Four Circumferential Sensors at each Axial Position

Number of Axial Sensor Rings	Average Error	Maximum Error	Standard Deviation
7	0.15	0.29	0.08
6	0.24	1.20	0.22
5	0.18	0.46	0.13
4	0.26	0.67	0.19
3	0.42	1.02	0.30
2	0.65	2.42	0.69

Table C.10 Average Absolute Error Using Average Profile Method and Three Circumferential Sensors at each Axial Position

Number of Axial Sensor Rings	Average Error	Maximum Error	Standard Deviation
7	0.29	0.99	0.25
6	0.28	0.85	0.20
5	0.16	0.65	0.15
4	0.30	0.77	0.19
3	0.37	1.10	0.32
2	0.51	1.74	0.43

Table C.11 Average Absolute Error Using Average Profile Method and Two Circumferential Sensors at each Axial Position

Number of Axial Sensor Rings	Average Error	Maximum Error	Standard Deviation
7	0.32	1.51	0.43
6	0.40	1.64	0.40
5	0.33	1.09	0.24
4	0.44	1.80	0.35
3	0.48	1.75	0.39
2	0.66	1.98	0.50

Appendix D

NEURAL NETWORK TRAINING AND RECALL PROFILES

Table D.1 contains the training and recall data used to develop a 2-D neural network model of the diffusion equation.

Table D.1 Neural Network Training Profiles

Training Profiles		Circumferential Position								
		1	2	3	4	5	6	7	8	9
Input #	1	599.2	599.2	599.2	599.2	599.2	599.2	599.2	599.2	599.2
Desired #	1	600.0	600.0	600.0	600.0	600.0	600.0	600.0	600.0	600.0
Input #	2	599.7	599.7	599.7	599.7	599.7	599.7	599.7	599.7	599.7
Desired #	2	600.5	600.5	600.5	600.5	600.5	600.5	600.5	600.5	600.5
Input #	3	600.2	600.2	600.2	600.2	600.2	600.2	600.2	600.2	600.2
Desired #	3	601.0	601.0	601.0	601.0	601.0	601.0	601.0	601.0	601.0
Input #	4	601.2	601.2	601.2	601.2	601.2	601.2	601.2	601.2	601.2
Desired #	4	602.0	602.0	602.0	602.0	602.0	602.0	602.0	602.0	602.0
Input #	5	602.2	602.2	602.2	602.2	602.2	602.2	602.2	602.2	602.2
Desired #	5	603.0	603.0	603.0	603.0	603.0	603.0	603.0	603.0	603.0
Input #	6	603.2	603.2	603.2	603.2	603.2	603.2	603.2	603.2	603.2
Desired #	6	604.0	604.0	604.0	604.0	604.0	604.0	604.0	604.0	604.0
Input #	7	604.2	604.2	604.2	604.2	604.2	604.2	604.2	604.2	604.2
Desired #	7	605.0	605.0	605.0	605.0	605.0	605.0	605.0	605.0	605.0
Input #	8	604.7	604.7	604.7	604.7	604.7	604.7	604.7	604.7	604.7
Desired #	8	605.5	605.5	605.5	605.5	605.5	605.5	605.5	605.5	605.5
Input #	9	605.2	605.2	605.2	605.2	605.2	605.2	605.2	605.2	605.2
Desired #	9	606.0	606.0	606.0	606.0	606.0	606.0	606.0	606.0	606.0

Table D.1 (Cont.)

Input #	10	606.2	606.2	606.2	606.2	606.2	606.2	606.2	606.2	606.2
Desired #	10	607.0	607.0	607.0	607.0	607.0	607.0	607.0	607.0	607.0
Input #	11	606.7	606.7	606.7	606.7	606.7	606.7	606.7	606.7	606.7
Desired #	11	607.5	607.5	607.5	607.5	607.5	607.5	607.5	607.5	607.5
Input #	12	607.2	607.2	607.2	607.2	607.2	607.2	607.2	607.2	607.2
Desired #	12	608.0	608.0	608.0	608.0	608.0	608.0	608.0	608.0	608.0
Input #	13	608.2	608.2	608.2	608.2	608.2	608.2	608.2	608.2	608.2
Desired #	13	609.0	609.0	609.0	609.0	609.0	609.0	609.0	609.0	609.0
Input #	14	609.2	609.2	609.2	609.2	609.2	609.2	609.2	609.2	609.2
Desired #	14	610.0	610.0	610.0	610.0	610.0	610.0	610.0	610.0	610.0
Input #	15	608.0	607.8	607.0	606.2	605.2	604.1	602.8	601.9	601.5
Desired #	15	609.0	610.0	608.0	606.0	607.5	605.0	603.0	602.0	601.0
Input #	16	606.3	606.6	607.2	607.7	608.0	607.7	607.2	606.6	606.3
Desired #	16	606.0	607.0	608.0	609.0	610.0	609.0	608.0	607.0	606.0
Input #	17	602.1	602.7	604.0	605.4	606.0	605.4	604.0	602.7	602.1
Desired #	17	601.0	602.0	605.0	607.0	610.0	607.0	605.0	602.0	601.0
Input #	18	606.8	606.3	605.2	604.0	603.5	604.0	605.2	606.3	606.8
Desired #	18	610.0	608.0	606.0	604.0	602.0	604.0	606.0	608.0	610.0
Input #	19	602.1	602.7	604.0	605.4	606.0	605.4	604.0	602.7	602.1
Desired #	19	600.6	602.3	604.9	607.1	609.8	607.0	605.2	601.8	601.5
Input #	20	605.7	605.6	605.1	604.2	603.8	604.1	604.5	604.9	605.0
Desired #	20	604.9	608.2	606.9	604.6	600.5	608.3	603.0	607.7	605.0
Input #	21	607.3	607.0	606.3	605.3	604.1	603.0	602.5	602.3	602.3
Desired #	21	608.8	609.2	606.1	607.2	606.3	600.1	604.6	602.3	603.5
Input #	22	601.8	602.1	603.0	603.9	604.4	604.4	603.9	603.1	602.8
Desired #	22	602.3	602.2	601.8	608.5	603.7	606.8	606.5	600.8	604.8
Input #	23	603.0	602.6	601.7	601.0	600.9	601.1	601.6	601.9	602.1
Desired #	23	606.0	603.9	602.1	600.7	601.3	601.3	603.2	602.4	604.2
Input #	24	605.4	605.3	604.8	604.2	603.9	603.7	604.1	605.0	605.6
Desired #	24	606.1	606.4	608.0	601.7	605.8	605.4	600.2	608.7	607.9
Input #	25	601.8	602.1	602.4	602.3	602.4	603.2	604.3	604.8	604.7
Desired #	25	600.4	602.6	605.9	602.2	602.4	600.4	609.7	606.8	602.4
Input #	26	605.1	605.1	604.8	604.6	604.9	605.1	604.2	603.1	602.7
Desired #	26	607.6	604.1	609.6	600.4	606.8	609.4	605.6	600.8	604.3
Input #	27	605.5	605.4	605.3	605.3	605.2	604.7	603.9	603.3	603.1
Desired #	27	608.8	604.3	607.5	605.0	607.6	605.2	605.9	601.2	605.7
Input #	28	606.2	606.4	606.6	606.1	605.3	605.0	605.0	604.8	604.5
Desired #	28	606.4	606.2	609.6	608.4	604.8	603.0	609.0	606.0	602.2
Input #	29	606.2	606.2	606.1	605.7	605.1	604.7	604.7	604.6	604.5
Desired #	29	607.5	606.6	607.7	607.0	607.0	601.1	609.6	603.5	606.0

Table D.1 (Cont.)

Input #	30	601.9	601.9	602.2	602.4	602.0	601.6	602.0	602.7	603.0
Desired #	30	603.2	602.7	600.6	607.7	601.6	600.3	602.2	605.7	603.2
Input #	31	605.3	605.6	605.7	605.0	604.2	604.3	605.3	606.3	606.6
Desired #	31	601.9	608.4	607.2	608.6	601.3	602.5	607.9	608.6	607.1
Input #	32	604.2	604.2	604.0	603.9	603.8	603.7	604.0	604.0	603.9
Desired #	32	602.0	607.8	604.4	602.8	608.0	600.1	607.5	605.7	602.4
Input #	33	603.4	603.8	605.0	606.2	606.8	606.8	606.6	606.3	606.2
Desired #	33	605.0	601.4	606.5	608.8	607.8	608.8	606.4	608.0	605.6
Input #	34	604.1	604.2	604.6	605.1	605.3	604.7	604.1	604.3	604.5
Desired #	34	601.5	607.6	602.8	606.6	609.5	605.1	601.0	607.6	604.7
Input #	35	604.7	604.8	605.3	605.6	605.2	604.7	605.0	605.9	606.4
Desired #	35	605.4	604.8	606.4	606.7	609.9	600.2	605.7	608.2	608.4
Input #	36	602.5	602.6	602.6	602.5	602.3	602.2	602.2	602.2	602.0
Desired #	36	601.7	604.9	601.8	605.9	601.3	602.9	603.6	604.2	600.4

Table D.2 Neural Network Recall Profiles

Recall Profiles		Circumferential Position								
		1	2	3	4	5	6	7	8	9
Input #	1	600.66	600.66	600.66	600.66	600.66	600.66	600.66	600.66	600.66
Desired #	1	601.50	601.50	601.50	601.50	601.50	601.50	601.50	601.50	601.50
Actual #	1	601.20	601.49	601.24	601.31	601.55	601.35	601.51	601.41	601.18
Error #	1	0.30	0.01	0.26	0.19	-0.05	0.15	-0.01	0.09	0.32
Input #	2	601.66	601.66	601.66	601.66	601.66	601.66	601.66	601.66	601.66
Desired #	2	602.50	602.50	602.50	602.50	602.50	602.50	602.50	602.50	602.50
Actual #	2	602.42	602.39	602.31	602.55	602.54	602.58	602.59	602.45	602.34
Error #	2	0.08	0.11	0.19	-0.05	-0.04	-0.08	-0.09	0.05	0.16
Input #	3	602.66	602.66	602.66	602.66	602.66	602.66	602.66	602.66	602.66
Desired #	3	603.50	603.50	603.50	603.50	603.50	603.50	603.50	603.50	603.50
Actual #	3	603.52	603.43	603.55	603.80	603.13	603.76	603.40	603.38	603.83
Error #	3	-0.02	0.07	-0.05	-0.30	0.37	-0.26	0.10	0.12	-0.33
Input #	4	603.66	603.66	603.66	603.66	603.66	603.66	603.66	603.66	603.66
Desired #	4	604.50	604.50	604.50	604.50	604.50	604.50	604.50	604.50	604.50
Actual #	4	602.74	605.96	603.88	604.08	605.60	603.10	605.38	604.35	604.20
Error #	4	1.76	-1.46	0.62	0.42	-1.10	1.40	-0.88	0.15	0.30
Input #	5	606.79	607.03	607.55	608.03	608.21	608.03	607.55	607.03	606.79
Desired #	5	606.50	607.50	608.50	609.50	609.50	609.50	608.50	607.50	606.50
Actual #	5	605.15	608.46	607.82	609.37	609.24	609.48	608.33	607.75	606.49
Error #	5	1.35	-0.96	0.68	0.13	0.26	0.02	0.17	-0.25	0.01

Table D.2 (Cont.)

Input #	6	603.97	604.45	605.55	606.61	607.04	606.61	605.55	604.45	603.97
Desired #	6	602.50	604.50	606.50	608.50	609.50	608.50	606.50	604.50	602.50
Actual #	6	603.51	602.99	607.74	607.27	609.84	607.53	606.86	604.79	601.97
Error #	6	-1.01	1.51	-1.24	1.23	-0.34	0.97	-0.36	-0.29	0.53
Input #	7	602.58	603.12	604.41	605.70	606.24	605.70	604.41	603.11	602.58
Desired #	7	601.50	602.50	605.50	607.50	609.50	607.50	605.50	602.50	601.50
Actual #	7	600.54	604.15	604.09	607.75	609.75	606.68	606.57	601.79	601.76
Error #	7	0.96	-1.65	1.41	-0.25	-0.25	0.82	-1.07	0.71	-0.26
Input #	8	603.66	603.66	603.66	603.66	603.66	603.66	603.66	603.66	603.66
Desired #	8	604.50	604.50	604.50	604.50	604.50	604.50	604.50	604.50	604.50
Actual #	8	602.74	605.96	603.89	604.08	605.60	603.10	605.38	604.35	604.20
Error #	8	1.76	-1.46	0.61	0.42	-1.10	1.40	-0.88	0.15	0.30
Input #	9	604.25	604.14	604.14	604.31	604.41	604.72	605.30	605.97	606.29
Desired #	9	606.22	605.34	601.69	609.76	600.94	608.02	603.65	608.70	607.63
Actual #	9	606.51	605.05	601.68	609.31	600.16	608.28	603.57	608.71	607.42
Error #	9	-0.29	0.29	0.01	0.45	0.78	-0.26	0.08	-0.01	0.21
Input #	10	604.98	604.95	604.94	604.67	604.17	604.18	605.04	605.89	606.16
Desired #	10	609.17	602.93	607.39	606.47	604.62	601.28	606.95	609.21	605.44
Actual #	10	607.86	603.81	606.71	606.96	604.98	600.78	607.48	608.75	606.37
Error #	10	1.31	-0.88	0.68	-0.49	-0.36	0.50	-0.53	0.46	-0.93
Input #	11	606.09	605.68	604.63	603.74	603.95	605.06	605.82	605.74	605.56
Desired #	11	607.79	608.05	605.76	602.23	601.67	607.54	609.95	604.84	606.53
Actual #	11	607.95	608.35	605.81	602.30	601.78	607.75	609.33	605.03	606.58
Error #	11	-0.16	-0.30	-0.05	-0.07	-0.11	-0.21	0.62	-0.19	-0.05
Input #	12	604.31	604.58	605.20	605.78	606.05	606.05	605.95	605.67	605.45
Desired #	12	604.65	604.20	606.85	606.57	608.42	605.62	607.57	607.98	602.77
Actual #	12	604.33	604.18	606.70	606.81	608.23	605.85	607.67	607.51	602.94
Error #	12	0.32	0.02	0.15	-0.24	0.19	-0.23	-0.10	0.47	-0.17
Input #	13	600.70	600.96	601.89	603.38	604.72	605.37	605.23	604.63	604.26
Desired #	13	601.37	601.03	600.19	606.03	605.67	608.72	605.41	607.61	600.11
Actual #	13	601.29	601.25	600.39	606.05	605.60	608.67	605.47	607.46	600.23
Error #	13	0.08	-0.22	-0.20	-0.02	0.07	0.05	-0.06	0.15	-0.12
Input #	14	603.49	603.99	605.16	606.32	606.82	606.32	605.15	603.99	603.49
Desired #	14	602.00	604.00	606.00	608.00	610.00	608.00	606.00	604.00	602.00
Actual #	14	601.95	604.02	605.94	607.90	609.81	607.94	605.95	604.11	601.75
Error #	14	0.05	-0.02	0.06	0.10	0.19	0.06	0.05	-0.11	0.25

Appendix E

THEORETICAL CALCULATIONS AND FE DATA FILES

A1.) Calculating Fluid Velocity and Reynolds Number of RCS

RCS Flow Rate(gpm) = $9.50\text{E}+04$
Q (ft³/s) = $2.12\text{E}+02$
Pipe Diameter(ft) = $2.67\text{E}+00$
Area(ft²) = $5.59\text{E}+00$
Velocity(ft/s) = $3.79\text{E}+01$
g (ft/s³) = $3.22\text{E}+01$
m' (lbs/s) = $1.32\text{E}+04$
Cv (BTU/lbm-F) = $4.74\text{E}-04$

Reynolds No. Calculations

rho(slugs/ft³) = $6.03\text{E}-2$
Velocity(ft/s) = $3.79\text{E}+01$
Pipe Diameter(ft) = $2.67\text{E}+00$
Mu(lbf-s/ft²) = $1.75\text{E}-06$
Reynolds number = $3.48\text{E}+06$

A2.) Calculating Fluid Velocity and Reynolds Number of Apparatus

RCS Flow Rate(gpm) = $4.00\text{E}+00$
Q (ft³/s) = $8.91\text{E}-03$
Pipe Diameter(ft) = $7.29\text{E}-02$
Area(ft²) = $4.18\text{E}-03$
Velocity(ft/s) = $2.13\text{E}+00$
g (ft/s³) = $3.22\text{E}+01$
m' (lbs/s) = $5.23\text{E}-01$
Cv (BTU/lbm-F) = $1.00\text{E}-03$

Reynolds No. Calculations

rho(slugs/ft³) = $5.67\text{E}-02$
Velocity(ft/s) = $2.13\text{E}+00$
Pipe Diameter(ft) = $7.29\text{E}-02$
Mu(lbf-s/ft²) = $1.36\text{E}-05$
Reynolds number = $6.48\text{E}+02$

B.1) HEAT LOSS IN RCS

$$T_a (F) = 1.00E+02$$

$$T_f (F) = 6.00E+02$$

$$\Delta T (F) = 5.00E+02$$

$$\text{Pipe Outside Diameter (in)} = 3.60E+01$$

$$\text{Pipe Inside Diameter (in)} = 3.20E+01$$

$$\text{Wall Thickness (in)} = 2.00E+00$$

Thermal Conduction through Pipe

$$(BTU/hr-ft-F) = 2.60E+01$$

$$\text{Insulation Thickness (in)} = 1.20E+01$$

$$\text{Insulation OD (in)} = 6.00E+01$$

Thermal Conduction through Insulation

$$(BTU/hr-ft-F) = 4.50E-02$$

$$\text{Mean Pipe Diameter (ft)} = 2.83E+00$$

$$\text{Mean Insulation Diameter (ft)} = 3.92E+00$$

Convective Coeffecient Calculation of Fluid

$$\text{Fluid Velocity (ft/s)} = 3.79E+01$$

$$\text{Fluid Temperature (F)} = 6.00E+02$$

$$\text{Inside Diameter (in)} = 3.20E+01$$

$$h_m [BTU/(hr)(ft^2)(F)] = 1.20E+04$$

Convective Coeffecient Calculation of Air

$$h_a [BTU/(hr)(ft^2)(F)] = 7.50E+00$$

Thermal Resistance Calculation

$$\text{Thermal Resistance (Rf)} = 9.93E-06$$

On Fluid Side

$$\text{Thermal Resistance (Rw)} = 7.20E-04$$

Of Steel Wall

$$\text{Thermal Resistance (Ri)} = 1.81E+00$$

Of Insulation

$$\text{Thermal Resistance (Ra)} = 8.13E-04$$

On Ambient Side

$$\text{Total Resistance} = 1.81E+00$$

$$q (BTU/hr) = 2.77E+02$$

Bulk Temperature Change per Foot

$$\Delta T_b/ft = 9.92E-06$$

B.2) Heat Loss in Apparatus

$$T_a (F) = 8.00E+01$$

$$T_f (F) = 1.15E+02$$

$$\Delta T (F) = 3.50E+01$$

$$\text{Pipe Outside Diameter (in)} = 1.00E+00$$

$$\text{Pipe Inside Diameter (in)} = 8.75E-01$$

$$\text{Wall Thickness (in)} = 6.25E-02$$

Thermal Conduction through Pipe

$$(BTU/hr-ft-F) = 2.60E+01$$

$$\text{Insul. Thickness (in)} = 1.00E+00$$

$$\text{Insulation OD (in)} = 3.00E+00$$

Thermal Conduction through Insulation

$$(BTU/hr-ft-F) = 4.50E-02$$

$$\text{Mean Pipe Diameter (ft)} = 7.80E-02$$

$$\text{Mean Insulation Dia. (ft)} = 1.52E-01$$

Convective Coefficient of Fluid

$$\text{Fluid Velocity (ft/s)} = 2.13E+00$$

$$\text{Fluid Temp (F)} = 1.20E+02$$

$$\text{Inside Dia (in)} = 8.75E-01$$

$$h_m [BTU/(hr)(ft^2)(F)] = 4.00E+02$$

Convective Coefficient Calculation of Air

$$h_a [BTU/(hr)(ft^2)(F)] = 7.50E+00$$

Thermal Resistance Calculation

$$\text{Thermal Resistance (Rf)} = 1.09E-02$$

On Fluid Side

$$\text{Thermal Resistance (Rw)} = 8.16E-04$$

Of Steel Wall

$$\text{Thermal Resistance (Ri)} = 3.89E+00$$

Of Insulation

$$\text{Thermal Resistance (Ra)} = 1.05E+00$$

On Ambient Side

$$\text{Total Resistance} = 4.95E+00$$

$$q (BTU/hr) = 7.08E+00$$

Bulk Temperature Change/ft

$$\Delta T_b / ft = 1.35E-02$$

```

TITL
***** Experimental Pipe FE Model *****

TYPE [ K N NNODEL REFL NPR NTRAN NAXI NZSTR ]
      1 2 4 1. 2 2 3 0 0

PRIN [ NBUG(*) ]
      1 0 0 0 0 0

GRID [ FOR N ( XL XR(*) PR(*) ) NEM( PR * ) ]
      0.0364583333 0.04166666 0.8 0.0833333 1.25
4 4
      0.0 0.0364583333 0.8 0.0833333 1.25
4 4
      0.0364583333 0.0833333 0.0 0.0
      0.000000 0.00000 0.0833333 0.036458333
      0.0598958333 0.05892556510 0.00000 0.025779935
      0.000000 0.05892556510 0.0598958333 0.025779935

MATL [FOR MACRO(I), K(I)]
      1 26.00
      2 0.045
      3 0.045
      4 26.00

ROBN [NROB, NODE(*), (H(*), TR(*))]
      18 0 2
      9 18
      1 10 19 28 37 46 55 64 73

      400.00 101.94
      400.00 103.30
      400.00 102.76
      400.00 101.86
      400.00 100.20
      400.00 103.31
      400.00 101.18
      400.00 103.09
      400.00 102.02

      9 18 27 36 45 54 63 72 81
      7.50 80.0000
      7.50 80.0000
      7.50 80.0000
      7.50 80.0000
      7.50 80.0000
      7.50 80.0000
      7.50 80.0000
      7.50 80.0000
      7.50 80.0000

FORM
SOLV
NORM
EXIT

```

Figure E.1 Example FEA Input File for the Piping of the Experimental Apparatus

```

TITL
***** Hot-Leg Pipe FE Model *****

TYPE [ K N NNODEL REFL NPR NTRAN NAXI NZSTR ]
      1 2 4   1. 2 2 3  0  0

PRIN [ NBUG(*) ]
      1 0 0 0 0 0

GRID [ FOR N ( XL XR(*) PR(*) ) NEM(PR *) ]
      1.3333333 1.50000 0.8 2.5 1.25
      4 4
      0.0      0.66666 0.8 1.25 1.25
      4 4
      1.333333 2.50000 2.16506 1.15407
      0.000000 0.00000 1.25000 0.66666
      1.916666 2.41482 1.65988 1.28790
      0.000000 0.64705 0.95833 0.34509

MATL [FOR MACRO(I), K(I)]
      1      7.500
      2      0.045
      3      0.045
      4      7.500

ROBN [NROB, NODE(*), (H(*), TR(*))]
      18 0 2
      9 18
      1 10 19 28 37 46 55 64 73
      12000.00 608.017
      12000.00 608.017
      12000.00 608.017
      12000.00 608.017
      12000.00 608.017
      12000.00 608.017
      12000.00 608.017
      12000.00 608.017
      12000.00 608.017
      12000.00 608.017

      9 18 27 36 45 54 63 72 81
      7.50 100.0000
      7.50 100.0000
      7.50 100.0000
      7.50 100.0000
      7.50 100.0000
      7.50 100.0000
      7.50 100.0000
      7.50 100.0000
      7.50 100.0000

FORM
SOLV
NORM
EXIT

```

Figure E.2 Example FEA Input File for the Hot-Leg Piping of the RCS

VITA

Logan Mullinix was born in Crossville, Tennessee on June 4, 1963. His parents are Joline Mullinix and the late Lester Mullinix of Jamestown, Tennessee. He is the second of three children the others being his older brother Larry and his younger sister, Marilyn.

In 1980 Logan began classes at Tennessee Technological University while a senior in high school at Alvin C. York Agricultural Institute and graduated with a degree in Mechanical Engineering. After obtaining his degree, Logan worked as a Project Engineer for an Original Equipment Manufacturer. In the spring of 1988, Logan enrolled at the University of Tennessee, Knoxville to study Artificial Intelligence and is currently seeking a Master's degree in Engineering Science.

Logan is a member of the American Society of Mechanical Engineers and the Society of Automotive Engineers.