IMPROVING THE CROSS CORRELATION METHOD OF INDIRECT FLOW MEASUREMENT BY WATER INJECTION AND MODELING

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ABSTRACT

This paper presents a technique to improve the Cross Correlation Function (CCF) method for indirect flow measurement. Unlike other methods, the CCF method does not need a specific instrument or tool for flow measurements. Instead, the delay time between two sensors can be derived by applying the CCF. A water flow loop was constructed to investigate the CCF method for flow measurement. Because the inherent process temperature variations were small when compared to significant amounts of measurement and process noise, inaccurate flow measurements were obtained. The performance of the CCF method could be improved by increasing the system signal-to-noise ratio, which is the process noise divided by the measurement noise. For this reason, a periodic injection of different temperature water was used to increase the process temperature variation. The results were favorable. However, several design variables needed to be selected. To assist, a CFD simulation was utilized to optimize the distance between sensors and injection point, the rate of injection flow, and other related variables. The results show that CCF optimization of these variables produces better flow measurement performance over a range of flow velocities.

Key Words: Cross Correlation, Flow measurement, CFD simulation, Noise analysis

1 INTRODUCTION

New instrumentation and control challenges arise with the advent of newer, safer, and more integral nuclear reactor designs. One such challenge is developing methods to characterize flow in non-traditional channels such as pool-type primary systems. Most of the light-water reactors (LWRs) in today's fleet have traditional piping that allows for direct measurement of coolant flow rate. These direct flow measurement methods include Venturi flow meters, magnetic flow meters, and differential pressure (DP) orifice plates. Pool-type primary systems do not have piping systems that allow for direct measurement of flow rate. Instead, the primary flow rate must be characterized through related measurements and inferential flow methods. There are several methods of inferential flow measurement including sensor signal cross-correlation, pump motor current signature analysis, and calorimetric analysis (heat balance). This paper focuses on cross-correlation analysis of temperature sensors to infer flow velocity.

The Cross Correlation Function (CCF) method is an indirect and innovative approach of measuring the flow rate by using the correlation among the signal noise, and was first introduced for NPP applications in the 1980s [1], which could be applied in the NPP online monitoring system for early anomaly detection [2]. The main difference in the CCF method when compared to all others previously listed is that it does not require any specific flow measurement instruments.

The basic idea of this method is to calculate the transit time between two sensors by using correlations between signals. Signal correlation analysis has been proposed and studied for flow characterization for many years [3] [4]. Povey applied this method to measure gas flow rates [5]. Ruan integrated the CCF method with neural networks for improved measurement performance [6]. Por optimized the CCF method by using the impulse response function for extremely low velocity flow measurement [7]. Signal correlation analysis uses the cross correlation of two co-located, redundant sensors to find the delay time between the sensors. Typically, thermocouples, Resistance Temperature Detectors (RTDs), or in-core neutron detectors are used for signal correlation. An NRC regulatory document (NUREG/CR-5501) presents the results of a signal correlation method using both simulated and experimental data [8]. The cross-correlation method investigation used both thermocouples and RTDs to estimate the transit time through cross-correlation of the process noise.

2 METHODOLOGY

This section will first describe the terminology and methodology behind the CCF method, the relationship between the noise ratio and overall performance of the CCF technique. The second part of this section will focus on the development of the CFD simulation model. Also, methods are introduced that are used to determine which configuration of model parameters would offer the most accurate flow measurement with the least amount of error.

2.1 Cross Correlation Function Method

To measure the flow rate using the CCF method, at least two parallel-located sensors are needed, hereafter called Sensor X and Sensor Y. Recall that these sensors may be RTDs, thermocouples, or some other non-flow related physical measurement. Using the data collected from these sensors, the CCF is calculated and then used to determine the delay time between X and Y. Given that the distance and the delay time between these sensors are known, the fluid velocity can then be calculated. A general scheme for the CCF method is shown next in Fig. 1.

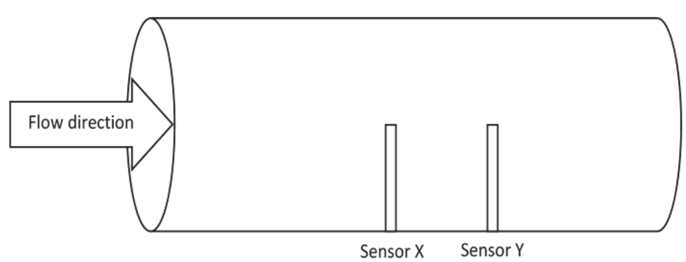

Figure 1. A brief scheme of CCF method

In the Fig. 1, the main flow moves from left to right, passing by X and Y. Though the example only shows two sensors, additional ones could be added along the pipe length to obtain additional correlation information. Fig. 2 provides a graphical representation of this method using the above scheme.

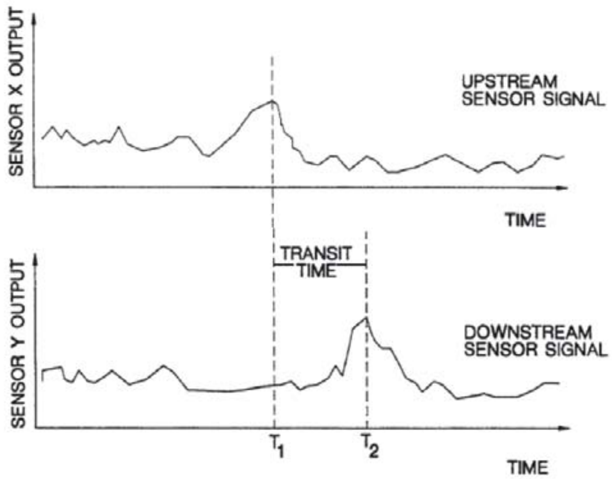

Figure 2. Sensor X and Y signal output versus time [8]

Fig. 2 indicates that the signals collected by sensors X and Y have an observable shift in signal behavior after the injection of some transient because of their position. If a peak is observed at time T_1 in the 1st sensor, the 2nd sensor detects this peak at a later time T_2. This is known as the delay or transit time between X and Y and is simply the difference between T_1 and T_2. If additional sensors were placed downstream of these two sensors, then the same peak would be observed at later times, but due to the fluid dynamics, the peak would be smaller in magnitude and may not be differentiable from process noise.

2.2 Verification of CCF method

To verify the CCF method, three temperature sensors were installed in a forced flow loop that was developed at the University of Tennessee Nuclear Engineering Department. Fig. 3 displays the full setup of the flow loop.

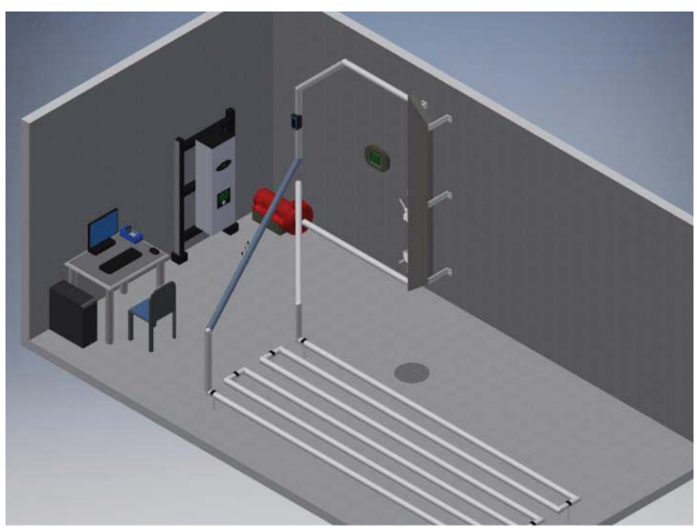

Figure 3. Forced flow loop setup [9]

The flow loop shown in Fig. 3 was constructed using 3-inch diameter PVC piping. A 7.5 HP Bell and Gossett pump, shown as the red object in Fig. 3, drives the flow loop. The blue section of pipe contains the thermocouples that are used for CCF measurement validation, while the grey down comer section contains a turbine flow meter. The pump is controlled by a Variable Frequency Drive (VFD), which is used to vary the speed of the pump from 15 Hz to 60 Hz. This range of pump speeds allows for main flow rates ranging from 0.004 - 0.02 m^3/s. The main flow is forced by the VFD pump and flows through the long section of pipes shown at the bottom of Fig. 3. This long section allows for most of the bubbles in the flow to be reabsorbed before the reaching the CCF measurement section. The flow then goes through the ultrasonic flow meter section and returns to the pump inlet. The CCF measurement portion of the flow loop is outlined next in Fig. 4.

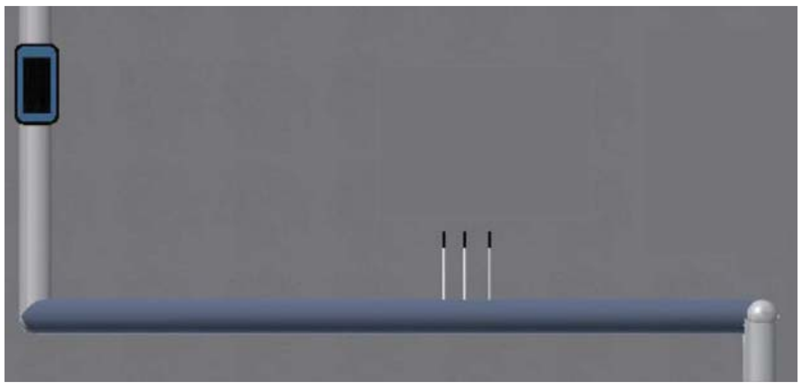

Figure 4. The test section in the flow loop [9]

The turbine flow meter is shown on the far left in Fig. 4, which is connected to the PVC piping. The blue pipe represents transparent PVC that is used to visually observe if there are bubbles in the flow or not. The bubbles would affect the measurements taken by the three vertical thermocouples and. the overall CCF measurement. An example of CCF flow measurement is shown in Fig. 5.

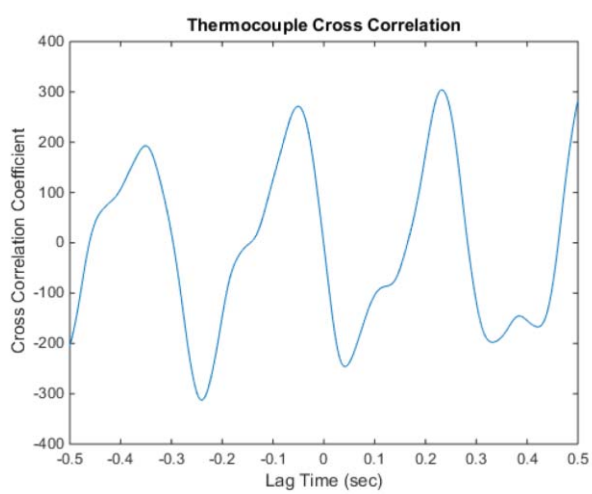

Figure 5: Thermocouple cross correlation as a function of lag time [9]

In the previous figure, the cross-correlation coefficient between two thermocouples exhibits an oscillatory behavior. There is consistently about a 0.25 second period (±10%) between thermocouple cross correlation coefficient peaks no matter the speed of the flow or the distance between thermocouples (6 or 12 inches). The result suggests that the observable correlation between thermocouples is unable to properly estimate the transport delay time.

2.3 Signal-to-noise ratio

This section provides a mathematical treatment of the CCF method. The temperature data recorded by sensors X and Y can also be defined as functions *x(t)* and *y(t)*, respectively. These functions are based on process values and noise, as well as measurement noise. These functions are shown in Equation 1 [10].

$$\begin{aligned} x(t) &= z(t) + n_x(t) \\ y(t) &= Cz(t-D) + n_y(t) \end{aligned} \tag{1}$$

In Equation (1), *z(t)* is the process temperature and the process noise at time *t*. C is a constant number to indicate the difference of *z(t)* between sensors X and Y. The functions $n_x(t)$, $n_y(t)$ are uncorrelated measurement noise, and *D* is the transport delay between *x(t)* and *y(t)*. The variables *x(t)* and *y(t)* are used in the calculation of the standard CCF, termed R_{xy} and shown next in Equation (2) [10].

$$R_{xy}(\tau) = \frac{1}{T}\int_0^T x(t)y(t+\tau)dt \tag{2}$$

In (2), the variable τ is the time lag used to calculate the CCF between *x(t)* and a delayed version of *y(t)* over a time period T. Substituting (1) into (2) is used to eliminate the measurement noise and results in a simplified CCF, shown next in Equation 3 [10].

$$R_{xy}(\tau) = \frac{1}{T}\int_0^T z(t)[z(t-D+\tau)]dt = R_{zz}(\tau - D) \tag{3}$$

In the previous equation, R_{xy} is now a function that is based on the process values and noise *z(t)* and a time lagged version of itself that includes the transport delay time *D*. This means that the simplified CCF in (3) is actually an auto correlation function of *z(t)* that also incorporates the delay time *D*. R_{xy} reaches a maximum when the argument $(\tau\text{-}D)$ is zero, that is, $R_{zz}(0)$ is a maximum when $\tau = D$. The time at which the CCF in the above figure reaches a maximum (or peak) is the transport delay *D*, which is the transit time and is used to find the fluid velocity. This is shown graphically in Fig. 6.

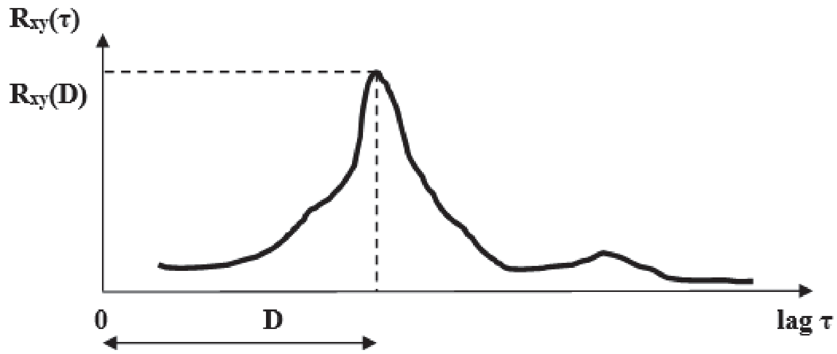

Figure 6. Cross correlation of Sensor X and Y signal output [10]

As discussed above, there are two different sources of noise: process noise and measurement noise. The process noise is the small fluctuation in temperature as the fluid flows through the main pipe. The measurement noise is composed of random noise components, generated by the electronic noise in the sensor and emf affecting the measurement process. From Equations (2) and (3), it is seen that the process noise is the major contributor in determining the delay time. Therefore, the measurement noise should be reduced as much as possible. To illustrate this assumption, a few manually generated signals with different magnitudes of process and measurement noise were simulated in Matlab. The noise ratio considered is a specific parameter that is defined as the measurement noise divided by the process noise. In the simulation model, linear multipliers were added and varied to each input of the noise sources to create different ratios for testing. This was done prior to applying the CCF method to the simulation results to determine the effect of the noise ratio on the CCF and estimation error. This step was performed to better understand the relationship between process noise, measurement noise, and inferential sensor error. The various noise ratios used in the simulation, along with calculated error measures, are shown in Table 1.

Table 1. Signal to Noise Ratio Simulation Results for Time Domain Signal Correlation

Noise ratio (Measure/process)	**Average Time Estimate* (seconds)**	**Average RMSE Value* (seconds)**	**Average Percent Error* (%)**
1/1	0.6000	0	0
3/2	0.6000	0	0
2/1	0.6000	0	0
13/6	0.5999	0.0001	0.02
11/5	0.5996	0.0004	0.06
9/4	0.5993	0.0007	0.11
7/3	0.5983	0.0020	0.33
5/2	0.5917	0.0114	1.89
3/1	0.5211	0.1106	18.44
10/3	0.4596	0.1977	32.95
7/2	0.4404	0.2353	39.20
4/1	0.4001	0.2948	49.14
9/2	0.3890	0.3156	52.59
5/1	0.3802	0.3308	55.13
11/2	0.3803	0.3325	55.41
6/1	0.3821	0.3328	55.46
13/2	0.3763	0.3370	56.17
7/1	0.3788	0.3354	55.91

* Each range or average is the result of 10,000 trials.

The results shown in Table 1 were drawn using noise ratios greater than and equal to one. Ratios less than one (meaning the measured signal had more process noise than instrument noise) produce stronger correlation magnitudes at the exact delay time, which is 0.6 seconds. The error between the actual flow rate and the simulated CCF results is calculated as a Root Mean Squared Error (RMSE) and average percent error. When the noise ratio reaches 3, the time domain method of signal correlation begins to fail. It is seen that the average percent error is over 18% for this case and would give a very inaccurate estimate of the flow rate. As this noise ratio continues to increase, the error of the CCF method increases very quickly, thus rendering the method ineffective.

Recall that it was stated that the original CCF method applied in the flow loop (Fig. 4) was not satisfactory. The cross correlation coefficient was periodic, caused by the sensors' intrinsic measurement noise, which accounts for the large noise ratio. Thus, by either decreasing the measurement noise or increasing the process noise, the performance of this method could be improved. The measurement noise is related to the instrument itself and can only be improved as the technology improves. On the other hand, the process signal could be improved by manually adding additional temperature variation into the flow. Referring back to Fig. 1, one way to increase the process noise is to add a heater upstream from X and Y [9][11]. This was attempted, but the heat input had very little affect on the large flow and heat capacity of the water. This paper presents a new method to manually add additional process temperature variations into the temperature signals: injecting water at a different temperature upstream of the two temperature sensors. The injected water was used to directly raise the process signal. This will benefit the CCF flow measurement. This setup is shown in Fig. 7.

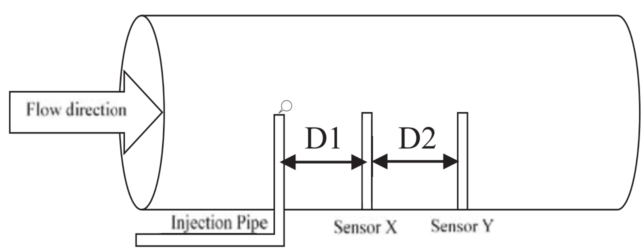

Figure 7. The CCF method with an injection pipe

2.4 CFD Simulation Model

Initial inferential flow measurement results using the physical test bed showed that the distances between flow insertion and the temperature sensors, the distance between temperature sensors, the flow pulse duration, and other variables had a large influence on the stability of the inferential flow estimate. Therefore, to optimize injection pipe and sensor placement, a CFD simulation of this setup was employed. The goal in using a CFD simulation is to determine how to improve the overall performance of the CCF method for flow measurement. This has the advantage of assigning the sensors, injection pipe and other related physical properties as variables that can be used in different configurations. The flow section shown in Fig. 7 was simulated using the Autodesk CFD software under ideal conditions with the main flow temperature set to 80 °F and at 1 atm pressure. Table 2 lists the six different variables that were used in the CFD model.

Table 2. Six variables to be optimized in CFD models

	6 variables to be optimized	Units
D1	Distance between injection pipe and the 1st sensor	Inch
D2	Distance between two sensors	Inch
INJ	Injection flow rate	GPM
T	Duration of injection period	s
TON	Injection-on time in one period	s
TEMP	Temperature of the infection flow	F

In the previous table, D1 and D2 are distance parameters related to the location of the injection pipe and sensors shown in Fig. 7. The injection flow rate INJ specifies how fast the heated water packets are injected into the main flow and T specifies the total duration of injections. Each simulation run has five total injection periods. In each injection period, that variable TON specifies the duration for each of the five injection periods in seconds. This variable can also be considered as the volume of each water packet. The last variable, TEMP, is the temperature of the injected water packets. For this simulation, heated packets were at 100 F, while other tests used cooled packets at 60 F. These two temperatures were used to determine if there was any difference in overall performance when using hot or cold injection. In industry, the cold injection might be preferred because the temperature of the hot leg is much higher than the cold leg. In this simulation, sensors X and Y are thermocouples and data is recorded every .01 seconds. Using these variables, separate configurations are tested to determine optimum model settings for flow rate measurement.

3 RESULTS

To determine which of the six variables listed in Table 2 influence the overall accuracy of the CCF method the most and which configuration could give a relatively precise measurement, several CFD models were developed. These separate models use different combinations of the defined variables. For each model, one of these dependent parameters is varied while the other five are held constant. This procedure is used to determine if varying these dependent variables has any effect on the efficacy of the CCF method. After these different configurations are programmed into each developed model, a transient event with a specific flow rate is applied for five injection periods. The sampling frequency used for all cases is 100 Hz.

During initial testing and simulation tuning, it was found that the CCF method could not measure certain flow rates. This is due to either unknown CFD software assumptions or because the established CCF flow measurement methodology was not applicable for certain flow rates. Since the temperature data is collected as a discrete signal, the time lag τ used to calculate the CCF is also a discrete number. That is, τ is only allowed to take on whole values. This means that the current CCF methodology was not found useful in the continuous case. For these current results, a specific flow rate is utilized to evaluate the performance of each case. The flow rate is based on the time delay between two sensors, and a parameter termed the Sampling Signal Number (SSN), defined in Equation (4).

$$SSN = \frac{D2}{V/SF} \tag{4}$$

Above, *D2* is the distance between two sensors, *V* is the flow velocity, and *SF* is the sampling frequency used in the simulation. The SSN is a constant which is multiplied by the number of time lags used to calculate the CCF. Therefore, the flow measurement could be directly determined by *SSN* when *D2* and *SF* are fixed. It is easier to evaluate each configuration by comparing the SSN instead of the flow velocity. Moreover, the SSN can be used as an additional performance metric to determine if the CCF method could obtain the correct flow rate. This means that the SSN calculated for that actual flow should be equal to the SSN obtained by the CCF method.

A large number of simulations has been carried out for both cold and hot injection studies, for brevity the hot injection results are shown in this paper. For the actual flow rate, the SSN is set at 7 for all cases. This will allow us to compare the SSN calculated from the CCF method. Relative results are listed in Table 3. In cases 1 to 7, D1 varies from 0.5 to 6. Recall that this variable is the distance from the injection point to the first sensor. Models with small values of D1 indicate that the CCF was accurate in obtaining flow measurement. Next, D2 is a critical variable because the calculation of the flow rate using the CCF is directly related to D2. In cases 8 to 11, this parameter is varied, and the results indicate that sensors placed very close or far apart will yield poor flow estimates using the CCF method. In cases 12 to 14, the results show that a small volume water packet injection would return unreliable flow estimates. Last, cases 15 to 23 indicate that varying the parameters T, TON or TEMP did not impact the CCF results. Then based on these results, further experiments should be carried out that vary the distances between injection point, sensor location and the volume of water packets injected.

Table 3: CCF method results (Sampling Frequency (SF) = 100Hz, Hot injection flow)

Case	D1	D2	INJ	T	TON	TEMP	True flow		CCF flow	
	Inch	Inch	GPM	s	s	F	GPM	SSN	GPM	SSN
1	0.5	2	0.05	4	1	100	52.46	7	52.46	7
2	1	2	0.05	4	1	100	52.46	7	52.46	7
3	2	2	0.05	4	1	100	52.46	7	52.46	7
4	3	2	0.05	4	1	100	52.46	7	52.46	7
5	4	2	0.05	4	1	100	52.46	7	61.20	6
6	5	2	0.05	4	1	100	52.46	7	52.46	7
7	6	2	0.05	4	1	100	52.46	7	91.80	4
8	2	0.5	0.05	4	1	100	13.11	7	11.47	8
9	2	1	0.05	4	1	100	26.23	7	26.23	7
10	2	2	0.05	4	1	100	52.46	7	52.46	7
11	2	3	0.05	4	1	100	78.69	7	91.80	6
12	2	2	0.02	4	1	100	52.46	7	61.20	6
13	2	2	0.05	4	1	100	52.46	7	52.46	7
14	2	2	0.08	4	1	100	52.46	7	52.46	7
15	2	2	0.05	3	1	100	52.46	7	52.46	7
16	2	2	0.05	4	1	100	52.46	7	52.46	7
17	2	2	0.05	5	1	100	52.46	7	52.46	7
18	2	2	0.05	4	0.5	100	52.46	7	52.46	7
19	2	2	0.05	4	1	100	52.46	7	52.46	7
20	2	2	0.05	4	1.5	100	52.46	7	52.46	7
21	2	2	0.05	4	1	90	52.46	7	52.46	7
22	2	2	0.05	4	1	100	52.46	7	52.46	7
23	2	2	0.05	4	1	110	52.46	7	52.46	7

Next, one of the better performing cases shown in Table 3 is selected for further analysis. Case 3 is chosen for this further analysis by varying the true flow rate while keeping all other simulation parameters constant. The SSN for the true flow rate was determined using Eqn. (4). This step is performed to determine if sensors, injection points and volumes are fixed, what ranges of flow rates can be accurately estimated by the CCF technique, shown in Table 4.

Table 4. Results based on the configuration of Case 3 with different main flow rate

Case	D1	D2	INJ	T	TON	TEMP	True flow		CCF flow	
	Inch	Inch	GPM	s	s	F	GPM	SSN	GPM	SSN
1	2	2	0.05	4	1	100	91.800	4	91.800	4
2	2	2	0.05	4	1	100	73.440	5	73.440	5
3	2	2	0.05	4	1	100	61.200	6	61.200	6
4	2	2	0.05	4	1	100	52.457	7	52.457	7
5	2	2	0.05	4	1	100	45.900	8	45.900	8
6	2	2	0.05	4	1	100	40.800	9	45.900	8
7	2	2	0.05	4	1	100	36.720	10	40.800	9
8	2	2	0.05	4	1	100	33.382	11	36.720	10
9	2	2	0.05	4	1	100	30.600	12	33.382	11
10	2	2	0.05	4	1	100	28.246	13	30.600	12

In the previous table, 10 separate cases are simulated using different flow rates that are based on using SSN values from 4 to 13. In cases 1 to 5, the CCF method is able to accurately estimate the true flow rate, which ranged from 45.9 to 91.8 GPM. However, for flow rates below 40 GPM, the CCF is unable to arrive at the correct flow rate. For example, case 6 used an actual flow rate of 40.8 GPM and the CCF method returned a value of 45.9 GPM, a difference of 5.1 GPM. While the difference of 5.1 GPM may not seem like a large error, actions taken in the NPP that are based on this error would cause a loss in efficiency. A possible reason for the deviation of these five cases is that the flow rate is too slow and maybe mixing occurs and reduces the temperature variations. Another reason could be that the turbulence changes the transport time. Possibly, sensors that have a higher sensitivity to temperature changes, such as RTDs, can be used instead of thermocouples to determine if these sensors provide better information for the CCF method. However, the faster response time of thermocouples may be more important than sensitivity to temperature changes. More research is needed to determine the answer.

As mentioned previously, one issue seen in the CCF method is that only integer values of τ can be used to arrive at flow estimates. For some flow regimes or rates, this can lead to very inaccurate answers. This also means that only integer values of the SSN can be used with the CCF method. For example, for a 50 GPM flow rate, the actual SSN calculated from Eqn. (4) is 7.34. The CCF estimate for this flow rate can only use an SSN of 7, which returns a flow rate of 52.46 GPM, a noticeable difference from the actual value. A faster sampling rate would result in better flow resolution; however, sampling rates for thermocouples are limited by the National Instruments thermocouple DAQ module at 100 samples/second.

Because the delay time is calculated as the maximum point of the CCF curve, a more accurate estimate of this point can increase the accuracy of flow estimates. Referring to Fig. 6, the plot of R_{xy} is composed of discrete integer points; application of a statistical regression technique might provide a better estimate of the maximum point of this curve. In Fig. 8, a portion of the CCF curve is shown, along with the estimates obtained by smoothing or regression fitting techniques.

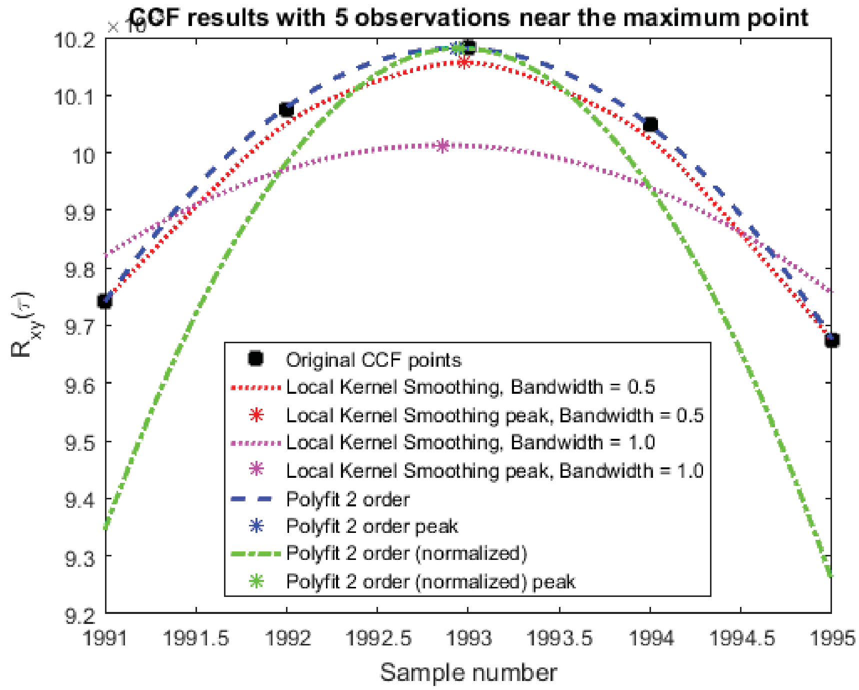

Figure 8. CCF results with 5 observations near the maximum point

In Fig. 8, the black points are the original CCF results, while the red and magenta dashed lines are two kernel smoothing of this result with different bandwidths. The blue/green lines are polynomial fits of the original CCF. The results show that when the bandwidth for the kernel regression is small enough, the fit could match the original CCF curve, while the unnormalized polynomial fit provides satisfactory answers as well. All the peaks are marked by asterisks, which can then be used to refine the models. Initial simulation results show that these techniques may be useful in better selecting the parameter *D2*, which could improve flow rate estimates.

4 CONCLUSIONS

This paper introduced a practical method to improve the accuracy of CCF measurement technique. Adding additional process variation through water packet injection improves the signal-to-noise ratio and provides a more accurate estimate of the actual flow using the CCF method. Also, CFD simulations can be used to optimize several parameters for designing CCF–based inferential flow measurement systems. The most relevant variables found to influence the CCF method were the distance from injection pipe to the first sensor, the distance between sensors, and volume of water injected. Initial results show that injection points placed too close or at a relatively large distance away from the first sensor would cause the CCF method to return inaccurate flow rate values. Also, the distance between sensors was found to be important, as sensors located at larger distances provided no useful information for the CCF method. This indicates that the transient caused by the injection activities has been masked by the fluid dynamics once it reaches the second sensor and therefore provided an unreasonable or unattainable value for the transport time. Finally, the volume of water was also an important variable, as low volume packets would be "lost" in the fluid dynamics even before being observed by the first sensor. CFD simulations can be used to optimize the setup based on the flow velocities of interest.

The improvement of CCF method is at an early stage. In this present research, only CFD simulations are utilized, which by themselves have no measurement noise inherent in the simulation dynamics. The simulation also assumes a temperature sensor with an immediate response. Based on these initial results, future research will include performing additional experiments on the forced-flow loop test bed using parameters optimized by the CFD analysis.

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