USAGE OF BUILDING ENERGY SIMULATION FOR HVAC FAULT DETECTION

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ABSTRACT

Building energy simulation can be powerful when it is combined with an implanted optimization function. The potential of this combination is tested and analyzed, using a simplified simulation program combined with a global optimization tool. The first test is automatic calibration of the building energy simulation model using global optimization. Automatic calibration can be helpful in quickly generating an accurate energy simulation model. The second test is fault detection of an HVAC system using the automatically calibrated simulation model and an optimization function. The experiments for the automatic calibration and fault detection are performed using simulation data. Small amounts of artificial noise are added to the simulation data to approximate model mis-specification. The method succesfully detected 75-85% of the faults tested when the noise levels present generate scatter in simulated heating and cooling data that approximates that observed in measured data. Hence it seems likely that the approach will often identify the fault but will need to be supplemented by site visits to complete the diagnosis.

INTRODUCTION

Previously reported fault detection methods have required the use of data from numerous sensors at the system or subsystem level (Piette et al., 2001), (Li and Braun 2002). The method introduced here requires only whole building heating, cooling and electricity consumption data and weather data. This data is used in conjunction with a building simulation program and a global optimization program to identify probable faults. This method requires far fewer sensors than required by most fault detection methods. Model mis-specification will lead to improper diagnosis in a significant portion of the cases, but an automated tool that is capable of correctly identifying problems that have manifest themselves only through a change in heating and cooling consumption would be of significant value. This is true, even if the diagnosis is correct only half or two-thirds of the time.

METHODOLOGY

Implementation of this fault detection process requires that a calibrated or "correct" model of normal system operation be developed initially.

The fault-detection process then seeks to find faulty HVAC system parameters by re-calibrating the "correct" model of normal system operation to fit the consumption data from the system when operating with a fault or faults. The changes in system parameters determined during the re-calibration process are then used to identify the system fault(s). The energy waste associated with the fault is determined by comparing the annual consumption predicted by the re-calibrated model with the annual consumption predicted by the original "correct" model of normal operation.

An automatic calibration method (Lee and Claridge 2002) is used to calibrate initial simulation and re-calibrate the simulation. This calibration method uses a Generalized Reduced Gradient (GRG) global optimization process. This ensures that the detection steps include iterations of all the possible variables included in the simulation.

The global optimization process minimizes the error between measured and simulated energy consumption. This approach to simulation model calibration was used by hydrological scientists to search for the location of water sources using a simulation model and several measured data points (e.g. Duan et al., 1992, Gupta et al., 1985, etc. etc.) but has not been used for energy simulations. The following objective function (1) is minimized in the auto-calibration of the HVAC energy simulations: where CHW_{sim} and HW_{sim} are cooling and heating consumption values generated by the simulation that is being calibrated and CHW_{mea} and HW_{mea} are the corresponding measured consumption values for the building being evaluated. It may be noted that the objective function is then the sum of the Root-Mean-Squared-Error (RMSE) of the simulated values of the cooling (CHW) and heating (HW) consumption.

$$Objective\_Function = Minimize\left(\frac{\sum_{i=1}^{n}\sqrt{(CHW_{sim}-CHW_{mea})^2}}{n-1} + \frac{\sum_{i=1}^{n}\sqrt{(HW_{sim}-HW_{mea})^2}}{n-1}\right) \quad ....(1)$$

The fault detection process is based on the mathematical relationships among the various variables and constants in the simulation model. This ensures that the fault detection procedure consider all the variables simultaneously. Several investigators (Gertler, 1998; Glass et al., 1994; Isermann, 1995; Patton et al., 1995; Salsbury et al., 2001) have proposed fault detection using simulation models of control systems. The method investigated in this paper uses an energy consumption simulation model and an optimization tool. The Solver® (Frontline Systems, 2000) package is one of the most advanced optimization tools available at relatively low cost and has capability to perform GRG global optimization. Multiple investigators have used this package to successfully avoid local minima that plague optimization procedures. Kahn-Jetter et al. (1997), Klukowski et al. (2001), and others have have successfully conducted research with Solver® in their own fields. Therefore this package (Solver®) was chosen to conduct an initial test of fault detection in the energy management field.

SIMULATION MODEL AND PROTOTYPE BUILDING

The simplified simulation model used here, which is a coding of the ASHRAE 'Simplified Energy Analysis Procedure' (Knebel, 1983), is used to investigate the possibility of fault detection through the optimization process. To test the automatic calibration performance of this approach, simulated heating and cooling energy consumption data for a prototype building is produced by the simulation model.

The prototype building used to generate the simulated energy consumption data is assumed to have a total conditioned area of 120,000 SF. Building length and width are 240 ft and 100 ft respectively. The height of the building is 65 ft with 5 floors. 13,260 SF of windows (30 % of 4 façade areas of the building) have a U-value of 1.1 Btu/h-ºF-SF . The remaining exterior sidewall area is 30,940 SF and the roof area is 24,000 SF. The wall U-value is 0.1 Btu/h-ºF-SF and the roof U-value is 0.05 Btu/h-ºF-SF. The occupancy of the building is 200 SF/person. Daily average lighting and receptacle electrical loads of 1.0 W/SF and 0.5 W/SF respectively, are assumed. The supply-air and outside-air flow rates are 1.2 cfm/SF and 0.12 cfm/SF respectively. The building is assumed to be equally split between interior and exterior zones. The occupancy schedule is assumed to be uniform for simplification. The range of average daily outside-air dry-bulb temperature is from 17 to 102ºF, while the average daily wet-bulb temperature swings from 15 to 78ºF. Room temperature is maintained at 73ºF by a single-duct-constant-volume (SDCV) terminal-reheat system. Since the packaged optimization program (Solver®) works with MS Excel® spreadsheet, the model is programmed using the same spreadsheet functions, and a programming language of Visual Basic for Application®, The total size of the program is 1.3 MB.

DATA INVESTIGATED

Simulated data and multiple synthetic faults are generated and used to test the automatic calibration and fault detection approach. The investigation reported here did not use measured energy consumption data from a real building or measured data from faulty HVAC systems. Instead, simulated energy consumption data generated by the simulation model was used to detect artificially created faults. There are two major advantages to using simulated data and artificially created faults for testing the fault detection approach. First, by using simulated data, both the original and the faulty HVAC operating parameters such as cooling coil temperature, cooling coil temperature, supply air volume etc. are known exactly. The results of the test can be determined accurately and conveniently. The other advantage of using the simulated data is that data for the faulty systems can be generated quickly and easily with little cost. This testing method does not include the modeling errors or sensor errors that are necessarily present when simulating a real building. This was approximated by adding random noise which is up to 10% of the average energy consumption to the simulated heating and cooling data. While this is only an approximation to sensor noise and modeling error, the degree of scatter that may be observed in simulated heating and cooling data with 5-10% random noise when plotted as a function of ambient temperature is comparable to the scatter often observed in similar plots of measured consumption data.

INITIAL MODEL CALIBRATION

The automatic calibration program uses the global optimization technique. This program is designed to calibrate the building energy performance model automatically. The number of parameters that require calibration was restricted to five for the work done here. The variables calibrated are Tcl (cooling coil leaving air temperature), Tr (room temperature), UAtot (overall coefficient of heat transfer multiplied by building envelope area), Vs (supply-air volume), and OA(%) (outside-air flow percentage). UAtot is the sum of UAwindow, UAroof and UAwalls. The boundaries of a set of reasonable values of parameters (Table 1) limit the variation of parameters for calibration in program.

Table 1.
The limiting values of parameters calibrated

	Max	Min
T_{cl} (°F)	70	45
T_r (°F)	80	60
UA_{tot} (Btu/h-ºF)	30,000	5,000
V_s (cfm/SF)	2.0	0.5
OA (%)	80	5

The initial parameter sets were generated within the bounds of Table 1 to test the calibration performance and identify any local minima. The 32 different initial-parameter-sets are composed of 5-parameter combinations of upper limit and lower limit values (Table 1), which correspond to extremely faulty initial input cases. Simulated data was generated using the "correct values" shown in Table 2 and 1% random noise was added to the simulated heating and cooling energy consumption. The presence of this noise results in an RMSE value of 5961.763 Btu/hr when the original input parameters were used. The results of 32 automatic calibrations to this data starting with the 32 possible extreme combinations of input data shown in Table 1 are summarised in Table 2.

Table 2
Automatic calibration results (average of 32 calibrations).

	Tcl	Tr	UA	Vsupply	OA(%)	RMSE
Units	(°F)	(°F)	(Btu/h-°F)	(cfm/sf)	(%)	(Btu/hr)
Correct Value	55.00	73.00	18,880.00	1.20	10.00	5,961.76
After Calibration	54.86	73.09	18,843.80	1.18	10.11	5,722.06
°F or (Calib.-Correct) / Correct x 100 (%)	0.14°F	0.09°F	0.2%	1.3%	1.1%	4.0%

FAULT DETECTION

A program was written to implement the test of the fault detection procedure that is reported herein. The program uses the global optimization technique to re-calibrate the formerly calibrated building energy performance model to the simulated energy consumption data for the faulty systems to find faulty parameters. The test restricted the number of parameters that may be varied in the calibration process to four. These are HVAC system parameters; T_{cl} (cooling coil leaving air temperature), T_r (room temperature), V_s (supply-air volume), and OA(%) (outside-air flow percentage).

The procedure for testing the fault detection method is composed of six steps. The first step generates the original HVAC operating parameters. This first step also includes inverse identification of the original HVAC system operation parameters from the simulated data with faulty parameter using the automatic calibration of the base simulation model. The details of the automatic calibration procedure used are explained in Figure 1. The second step imposes one or more artificial fault parameters in the model and generates the simulated energy consumption data.

The artificially generated synthetic faulty parameters are summarized in the left half of Table 4. The third step puts artificial noise on the simulated data. This step makes the simulated data more closely approximate real measured data. The noise simulates the model uncertainty present in real cases. For a real building, the simulation model cannot perfectly represent the real building behavior. Reddy et al. (1992) observed that a model is never "perfect", and invariably a certain amount of the observed variance in the response variable is unexplained by the model. The fourth step constitutes the main computational work required by the fault detection process. The global optimization program Solver® (Frontline Systems, 2000) minimizes the objective function defined in the methodology section. The minimization finds the HVAC operation parameters corresponding to the synthetic faulty parameters. The next step compares the HVAC operating parameters found in the first step with those from the fourth step. The differences are examined to check if they are large enough to be categorized as a fault or not. The thresholds for the faults assumed are based on errors often observed with pneumatic control system. Generating the results is the last step of the fault detection process.

FAULT DETECTION TEST RESULTS

120 sets of simulated data were tested. Each of 30 different sets of input parameters was modified by adding artificial noise levels of 1%, 3%, 6%, and 10% to give 120 sets of output. The results of the test are summarized in Table 3. The number of faults successfully detected are 118 out of 120 faulty parameters with 1% noise, 112 out of 120 with 3% noise, 102 out of 120 with 6% noise, and 94 out of 120 with 10% noise. These results are based on acceptable errors for each parameter defined as ±2.5°F for T_{cl}, ±1°F for T_r, ±0.2cfm/sf for V_s, and ±2.5% for OA(%). The mean bias errors for the four detected parameter values (T_{cl}, T_r, V_s, OA(%)) in all 120 cases are 0.35 (°F), 0.11 (°F), 0.03 (cfm), and –0.33 (%), respectively. Each detection process took less than 5 minutes with an ordinary Pentium III personal computer. The artificial noise on the simulated data, which represents model uncertainty and sensor noise, appears to contribute to the errors in the detected parameters. The dimmed cells in Table 4 are artificial fault parameters and detected fault parameters. The artificial fault parameters were +10°F and -10°F from the original setting of T_{cl}, ±5°F from the original T_r setpoint, –0.8cfm/SF from the original V_s, and +20% and –7% from the original OA(%). Those variations were selected to be within

Table 3
The summary of the fault detection test (Noise of 1%, 3%, 6%, and 10%).

		T_{cl} (°F)			T_r (°F)			V_s (cfm/SF)		OA (%)		
		Low	High	Correct	Low	High	Correct	Low	Correct	Low	High	Correct
Assigned	Value	45.0	65.0	55.0	68.0	78.0	73.0	0.4	1.2	3.0	30.0	10.0
Detected	Average	45.4	66.6	54.2	68.3	78.0	73.1	0.5	1.2	2.9	29.6	9.5
	Max	48.0	69.5	56.8	69.6	79.7	73.6	0.8	1.4	4.7	30.9	11.9
	Min	43.0	65.0	47.8	67.6	76.6	72.7	0.4	0.7	2.0	22.0	5.6
Tolerance	Max	50.0	70.0	60.0	70.0	80.0	75.0	0.8	1.6	8.0	35.0	15.0
	Min	40.0	60.0	50.0	66.0	76.0	71.0	0.0	0.8	0.0	25.0	5.0
# Out of tolerance / # of test		1/120			0/120			1/120		1/120		
Mean Bias Error		0.4			0.1			0.0		-0.3		

the physically possible range and to be large enough to lead to increased energy consumption or possibly to comfort problems. For example, the variation of –0.8cfm/SF for V_s might represent a loose supply fan belt . The results of the test are shown visually in Figures 2 through 5.

LOCAL MINIMA

The calibration process can sometimes produce simulated energy consumption values rather close to the measured consumption when incorrect input parameters are used. In terms of optimization, this corresponds to a local minimum. The program developed using Solver® can filter out the local minima solutions, which may be confused as correct solutions (Lee and Claridge 2002). However, earlier work using root-mean square optimization procedures for parameter identification from building energy data has sometimes found incorrect and unphysical results (Claridge et al., 1987, Reddy and Claridge, 1994). Hence further testing of this procedure with more variable model parameters, more complicated noise and with real building faults is recommended.

CONCLUSIONS

A fault detection method using an optimization technique, which has not been previously applied to whole building consumption data, is programmed and tested with a commercial optimization add-in function Solver®. The fault detection method provided objective (free from local minima), accurate, and rapid fault detection using the simulated building HVAC energy consumption in the 120 cases tested with acceptable fault detection parameters of ±5°F for T_{cl}, ±2°F for T_r, ±0.4cfm/SF for V_s, and ±5% for OA(%). The program successfully detected 118 out of 120 faulty parameters with 1% noise, 112 out of 120 with 3% noise, 102 out of 120 with 6% noise, and 94 out of 120 with 10% noise. These results are based on acceptable errors of ±2.5°F for T_{cl}, ±1°F for T_r, ±0.2cfm/SF for V_s, and ±2.5% for OA(%). Further testing of the method with more realistic sets of permitted faults, larger amounts of model mis-specification and with real building datais needed to determine whether this approach can succesfully identify faults from real building data.

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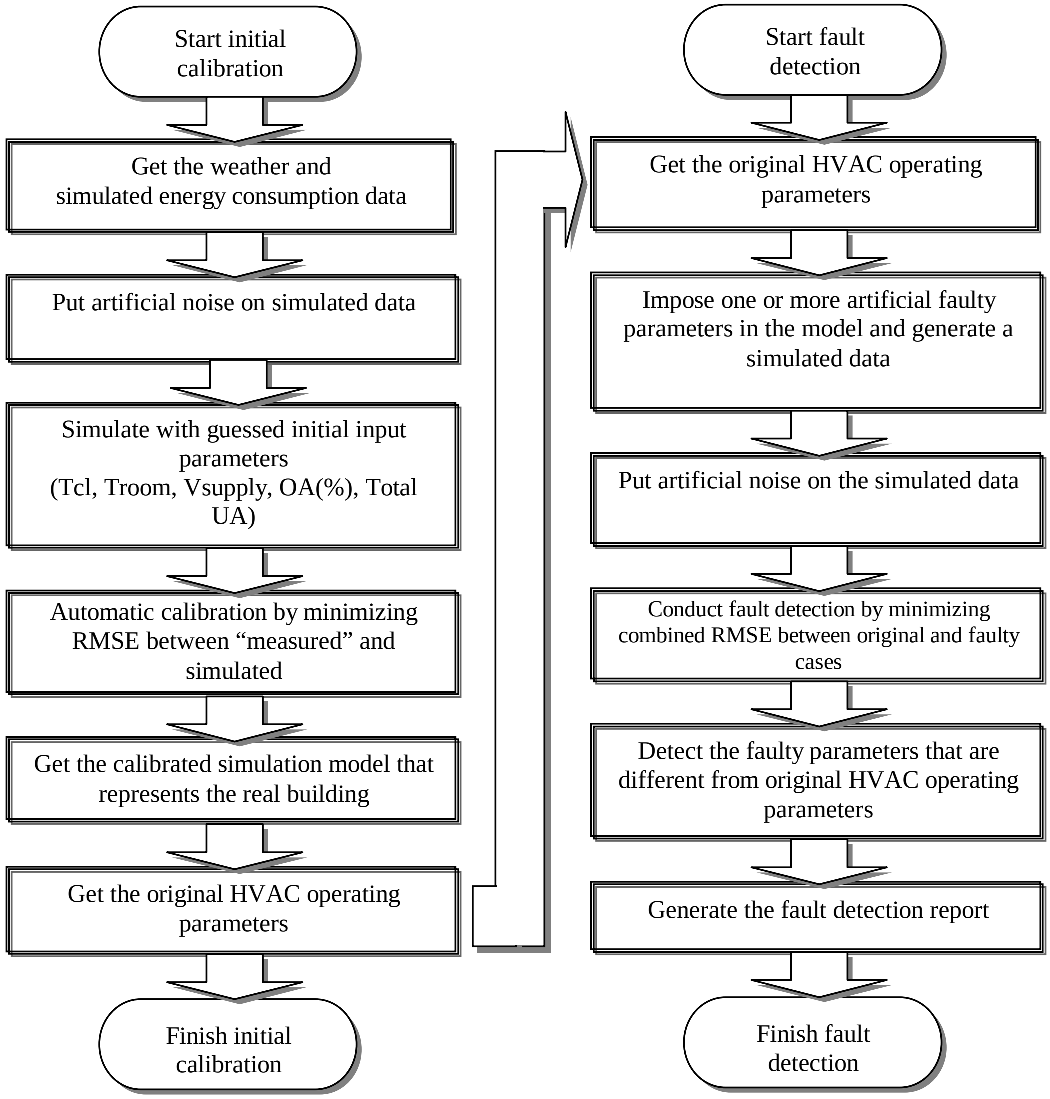

Figure 1
Automatic Calibration Procedure (left) & Fault Detection Procedure (right)

Table 4

Assigned and detected fault parameters with 10% artificial noise

10% Artificial Fault	Assigned Fault						Detected Fault					
	Test No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
One Variable Fault	1	45	73	1.2	10	2586413.8	1	44.4	73.6	1.15	10.4	57651.6
	2	55	78	1.2	10	1788140.6	2	51.2	79.7	0.96	11.9	56451.7
	3	55	73	0.4	10	1395312.3	3	56.8	72.7	0.46	9.2	58635.9
	4	55	73	1.2	30	1021912.8	4	54.7	73.4	1.16	30.9	57616.7

10% Artificial Fault	Assigned Fault						Detected Fault					
	Test No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
Two Variable Fault	5	45	68	1.2	10	1811586.3	5	44.4	68.6	1.14	10.5	57651.5
	6	65	68	1.2	10	1517156.4	6	65.8	69.1	1.20	10.1	58387.0
	7	45	73	0.4	10	1106302.2	7	48.0	73.1	0.45	9.3	57600.3
	8	65	73	0.4	10	1710798.7	8	68.6	72.9	0.78	5.9	57549.3
	9	45	73	1.2	3	2628635.0	9	47.7	73.2	1.32	2.9	57229.0
	10	65	73	1.2	30	542544.3	10	65.6	72.8	1.37	26.8	57195.7
	11	55	68	0.4	10	1577788.2	11	52.9	67.9	0.35	11.3	58416.2
	12	55	78	0.4	10	1219018.7	12	54.8	78.5	0.39	10.4	58164.4
	13	55	68	1.2	3	1001875.0	13	47.8	69.6	0.71	4.7	56424.1
	14	55	78	1.2	30	1673150.0	14	54.7	78.4	1.17	30.7	57616.7
	15	55	73	0.4	3	1463464.2	15	52.4	73.2	0.35	3.6	58032.3
	16	55	73	0.4	30	1212904.8	16	55.3	73.1	0.41	29.6	58663.7

10% Artificial Fault	Assigned Fault						Detected Fault					
	Test No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
Three Variable Fault	17	45	68	0.4	10	1254542.7	17	48.0	67.6	0.47	8.8	58000.6
	18	65	78	0.4	10	1572491.5	18	69.5	76.6	0.77	6.2	56069.0
	19	45	68	1.2	3	1853217.7	19	43.0	68.8	1.07	3.4	57735.5
	20	65	78	1.2	30	59617.6	20	65.0	78.2	1.20	30.0	58265.5
	21	55	68	0.4	3	1645993.1	21	52.9	67.9	0.35	3.6	58072.5
	22	55	78	0.4	30	1031535.6	22	54.7	78.5	0.39	30.9	58087.7
	23	45	73	0.4	30	865657.4	23	45.0	73.5	0.40	30.5	58016.3
	24	65	73	0.4	3	1747628.2	24	68.6	73.3	0.70	2.2	58445.1
	25	65	68	1.2	3	1705132.4	25	65.9	69.0	1.20	3.2	58576.0
	26	45	78	1.2	30	3419432.6	26	44.8	78.3	1.19	30.4	57651.5

10% Artificial Fault	Assigned Fault						Detected Fault					
	Test No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
Four Variable Fault	27	65	68	0.4	3	1882528.4	27	66.6	68.4	0.71	2.0	59002.2
	28	45	78	0.4	30	747652.6	28	44.6	78.6	0.39	30.8	57723.0
	29	65	78	0.4	3	1609367.3	29	69.5	77.3	0.69	2.3	57465.8
	30	65	78	0.4	30	1427994.9	30	67.4	76.8	0.58	22.0	56449.5

* The dimmed cells are assigned or detected fault parameters, others are original parameters and it's detected values.

* Circled values are unacceptable detection values.

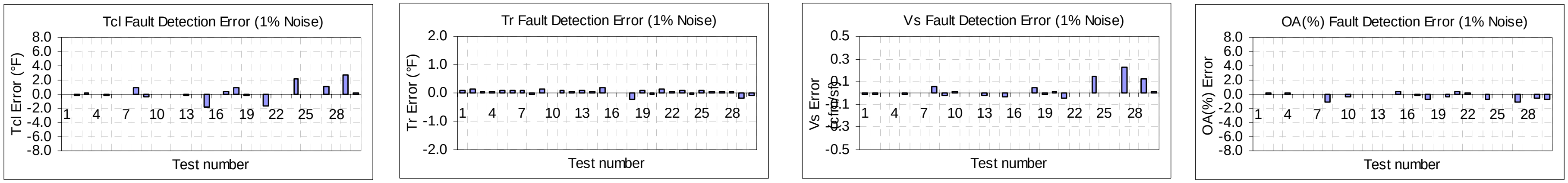

Figure 2. Error between assigned and detected fault parameters with 1% artificial noise.

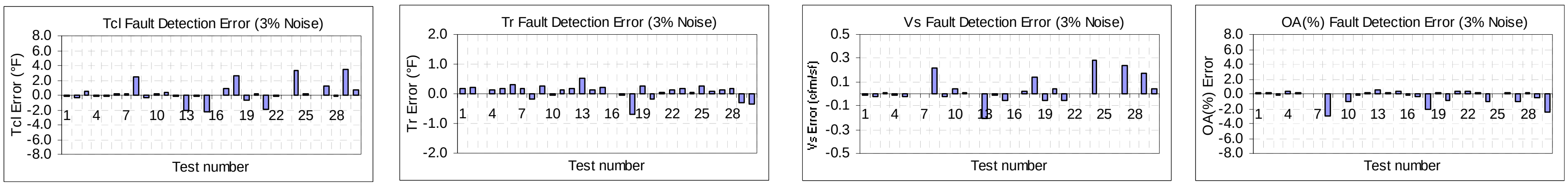

Figure 3. Error between assigned and detected fault parameters with 3% artificial noise.

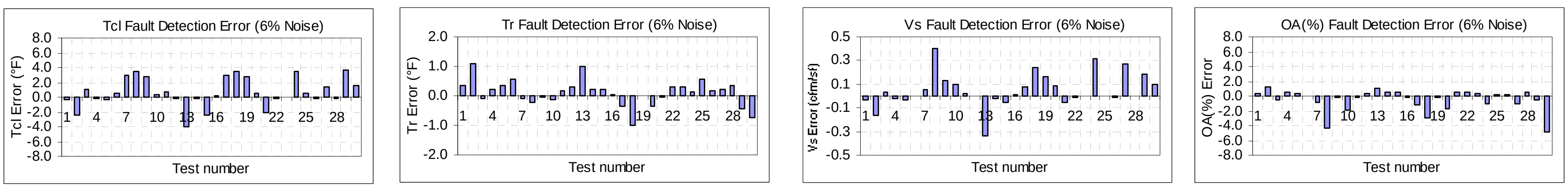

Figure 4. Error between assigned and detected fault parameters with 6% artificial noise.

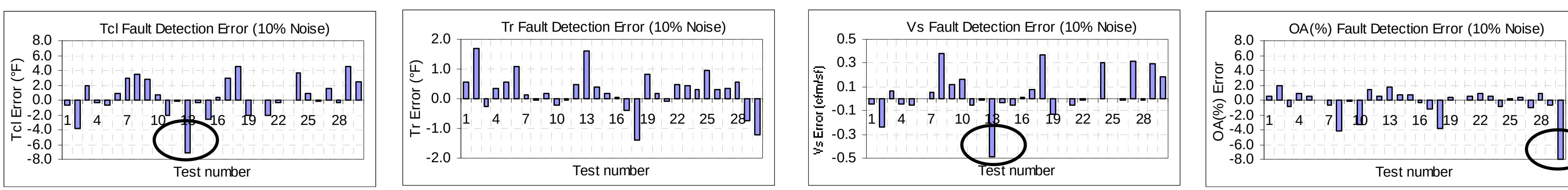

Figure 5. Error between assigned and detected fault parameters with 10% artificial noise.
** Circled values are unacceptable detection values.*