Remote Fault Detection of Building HVAC System Using a Global Optimization Program

Seung Uk Lee
Mechanical Engineer
ADM Associates, Inc.
Sacramento, CA

David E. Claridge, Ph.D., P.E.
Professor
Texas A&M University
Energy Systems Laboratory
College Station, TX

ABSTRACT

The energy efficiency of HVAC systems in buildings often degrades with the passage of time. Significant engineering time is normally required to determine the cause(s) of the degradation. This paper reports a preliminary investigation of a remote fault detection method using the global optimization program Solver® (Frontline Systems, 2000) coupled to a simplified simulation program, which is a coding of the ASHRAE 'Simplified Energy Analysis Procedure' (Knebel, 1983). This approach[1] uses the simulation program in conjunction with synthetic measured data to identify faults in the building operation. This fault detection approach has successfully identified all of the faulty parameters with noise levels of 1%, 3% and 6%. It successfully detected 117 of 120 faulty parameters in the presence of 10% noise. These results are based on acceptable errors for each parameter defined as ±5°F for Tcl, ±2°F for Tr, ±0.4cfm/sf for Vs, and ±5% for OA(%). If the acceptable errors for each parameter are reduced to ±2.5°F for Tcl, ±1°F for Tr, ±0.2cfm/sf for Vs, and ±2.5% for OA(%), the number of faults successfully detected decreases to 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 that were introduced into synthetic "measured data" that was generated with the simulation program.

INTRODUCTION

Previously reported remote 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 does not require the numerous sensors required by most fault detection methods. It has the potential to directly generate a report that identifies potential faults for the facility operator, including the projected annual cost of energy-waste associated with the fault.

METHODOLOGY

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

The remote 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 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 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 faulty 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 thoroughly tested by hydrological scientists in searches

[1] Software copyright © 2002

for the location of a water source using a simulation model and several measured data points (Duan et al., 1992, 1993, 1994), (Gupta et al., 1985, 1998, 1999), (Sorooshian et al., 1980, 1981, 1983, 1990, 1993). The hydrological scientists used the process to find correct x, y, and z coordinate values of water sources.

The following objective function is minimized in the auto-calibration of the HVAC energy simulations:

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

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.

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 steps 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. Multiple investigators have used this package to successfully avoid local minima that plague optimization procedures. Kahn-Jetter et al. (1997), Kane et al. (1997), Klukowski et al. (2001), Morrice et al. (2001), Nikitas et al. (2000, 2001) Okennedy et al. (1994), Thiriez (2001), and Walsh et al. (1995) all successfully conducted research with Solver® in their own fields. Therefore this package (Solver®) was chosen to conduct an initial test of remote 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 remote fault detection through the optimization process. To test the automatic calibration performance of this approach, "synthetic" measured heating and cooling energy consumption data for a prototype building is produced by the simulation model.

The prototype building used to generate the synthetic measured 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. Room temperature is maintained at 73 ºF by a single-duct-constant-volume (SDCV) terminal-reheat system.

SYNTHETIC DATA

Synthetic measured data and multiple synthetic faults are generated and used to test the 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 synthetic measured data and artificially created faults for testing the fault detection approach. First, by using synthetic 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 synthetic 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 synthetic measured heating and cooling data.

REMOTE FAULT DETECTION

A program was written to implement the test of the remote fault detection procedure that is reported herein. The program uses the global optimization technique to calibrate the building energy performance model to the synthetic measured 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. Those are Tcl (cooling coil leaving air temperature), Tr (room temperature), Vs (supply-air volume), and Xoa (outside-air flow fraction).

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 synthetic measured data using the automatic calibration of the base simulation model. The details of the automatic calibration procedure used are thoroughly explained in Lee and Claridge (2002). The second step imposes one or more artificial fault parameters in the model and generates the faulty synthetic measured data. The artificially generated synthetic faulty parameters are summarized in the left half of Tables A-1 through A-4 (APPENDIX A). The third step puts artificial noise on the synthetic measured data. This step makes the synthetic measured data more closely approximate real measured data. The noise represents the model uncertainty for the 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. Generating the results is the last step of the fault detection process.

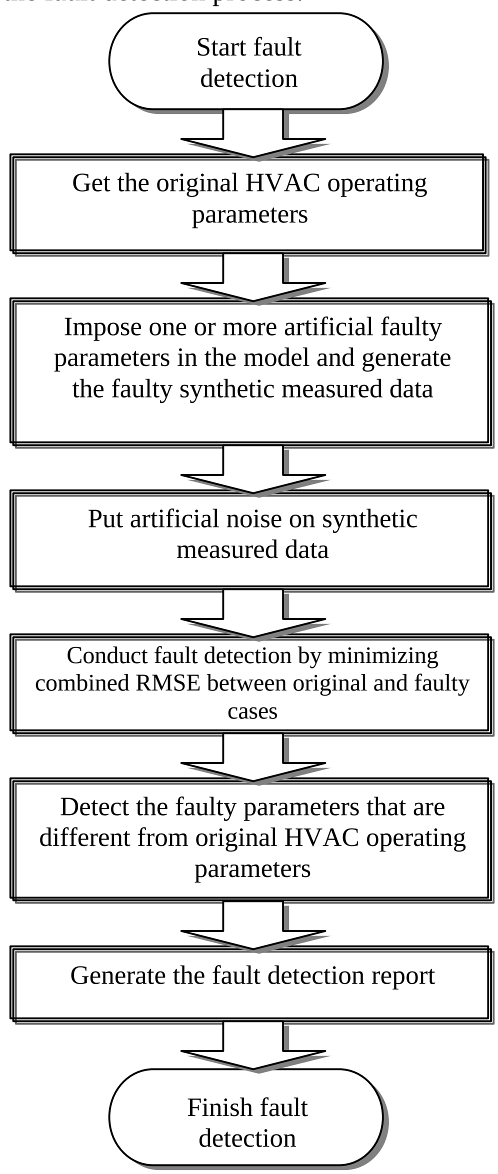

Figure 1. Remote fault detection procedure.

FAULT DETECTION TEST RESULTS

120 sets of synthetic data were generated using the different combinations of faulty parameters as shown in Tables A-1 through A-4 (APPENDIX A). Each of 30 different sets of input parameters generating output that 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 1. The program successfully detected all of the faulty parameters with noise levels of 1%, 3% and 6%. It successfully detected 117 of 120 faulty parameters in the presence of 10% noise. These results are based on acceptable errors for each parameter defined as ±5°F for Tcl, ±2°F for Tr, ±0.4cfm/sf for Vs, and ±5% for OA(%). If the acceptable errors for each parameter are reduced to ±2.5°F for Tcl, ±1°F for Tr, ±0.2cfm/sf for Vs, and ±2.5% for OA(%), the number of faults successfully detected decreases to 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.

The mean bias errors for the four detected parameter values (Tcl, Tr, Vs, 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 synthetic measured data, which represents model uncertainty and sensor noise, appears to contribute to the errors in the detected parameters. For each of Tables A-1 through A-4, the RMSE values for the same assigned faults are different due to the different levels of artificial noise. The dimmed cells on Tables A-1 through A-4 are artificial fault parameters and detected fault parameters. The artificial fault parameters were +10°F and -10°F from the original setting of Tcl, ±5°F from the original Tr setpoint, -0.8 cfm/ft^2 from the original Vs, and +20% and –7% from the original OA(%). Those variations were selected to be within the physically possible range and to be large enough to lead to increased energy consumption or possibly comfort problems. The results of the test are shown visually in Figures B-1 through B-4 (APPENDIX B).

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.

Table 1. The summary of the remote fault detection test.

		Tcl			Tr			Supply air		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		

CONCLUSIONS

A remote 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 remote fault detection method provided objective (free from local minima), accurate, and rapid fault detection using the synthetic "measured" building HVAC energy consumption in the 480 cases tested with acceptable fault detection parameters of ±5°F for Tcl, ±2°F for Tr, ±0.4cfm/sf for Vs, and ±5% for OA(%). If the acceptable fault detection criteria are tightened to ±2.5°F for Tcl, ±1°F for Tr, ±0.2cfm/sf for Vs, and ±2.5% for OA(%), the number of faults successfully detected then decreased to 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. Further testing of the method with more realistic sets of permitted faults, larger amounts of model mis-specification and with real building data appears warranted.

REFERENCES

Claridge, D. E., Bida, M., Krarti, M., Jeon, S., Hamzawi, E., Zwack, W. and Weiss, I., 1987. Ventilation of the Variable-Based Degree-Day Method, Final Report submitted to ASHRAE under Research Project RP-384, 139 pp.

Duan, Q.Y., Gupta, V.K., Sorooshian, S., 1993. Shuffled complex evolution approach for effective and efficient global minimization, J. Optimization Theory And Applications, 76 (3): 501-521.

Duan, Q.Y., Sorooshian, S., Gupta, V., 1992. Effective and efficient global optimization for conceptual rainfall-runoff models, Water Resources Res., 28 (4): 1015-1031.

Duan, Q.Y., Sorooshian, S., Gupta, V.K., 1994. Optimal use of the sce-ua global optimization method for calibrating watershed models, J. Hydrol., 158 (3-4): 265-284.

Frontline Systems, 2000. User Guide; Premium Solve Platform for use with Microsoft Excel, Frontline Systems, Inc., Incline Village, NV.

Gertler, J. 1998. Suervey of model-based failure detection and isolation in complex plants, IEEE Control Systems Magazine, 6 (8): 3

Glass, A., P. Gurber, M. Toos, J. Tödtli. 1994. Preliminary evaluation of a qualitative model-based fault detector for a central air-handling unit. Proceedings of 3rd IEEE Conference on Control Applications, Glasgow.

Gupta, A., 1998. Application of PC spreadsheet software for non-linear parameter optimization, J. Canadian Petroleum Technology, 37 (3): 51-54.

Gupta, H.V., Bastidas, L.A., Sorooshian, S., Shuttleworth, W.J., Yang, Z.L., 1999. Parameter estimation of a land surface scheme using multicriteria methods, J. Geophysical Research-Atmospheres, 104 (D16): 19491-19503.

Gupta, H.V., Sorooshian, S., Yapo, P.O., 1998. Toward improved calibration of hydrologic models: Multiple and noncommensurable measures of information, Water Resources Res., 34 (4): 751-763.

Gupta, V.K., Sorooshian, S., 1985. The automatic calibration of conceptual catchment models using derivative-based optimization algorithms, Water Resources Res., 21 (4): 473-485.

Gupta, V.K., Sorooshian, S., 1985. The relationship between data and the precision of parameter estimates of hydrologic-models, J. Hydrol., 81 (1-2): 57-77.

Isermann, R. 1995. Model-based fault detection and diagnosis methods, Proceedings of the American Control Conference, Seattle, Washington, 1605.

Kahn-Jetter, Z.L., Sasser, P.A., 1997. Using spreadsheets for studying machine design problems involving optimization, Computer Applications In Engineering Education, 5 (3): 199-211.

Kane, P., Diamond, D., 1997. Determination of ion-selective electrode characteristics by non-linear curve fitting, TALANTA, 44 (10): 1847-1858.

Klukowski, L., Kuba, E., 2001. Minimization of public debt servicing costs based on nonlinear mathematical programming approach Control And Cybernetics, 30 (1): 99-114.

Knebel, D.E., 1983. Simplified energy analysis using the modified bin method. Atlanta, GA: American Society of Heating, Refrigerating, and Air-conditioning Engineers. Inc.

Lee, S.U., Claridge, D.E., 2002. Automatic Calibration of a Building Energy Simulation Model Using a Global Optimization, Proc. of 2002 ICEBO, Richardson, Texas, pp. 159-164.

Lee, S.U., 2002. Automatic calibration of a building energy performance model and remote fault detection for continuous commissioningSM using a global optimization program, Master's Thesis, Texas A&M University, College Station, TX.

Li H., Braun J.E., 2002. On-line models for use in automated fault detection and diagnosis for HVAC&R equipment, ACEEE Summer Study on Energy Efficiency in Buildings, pp. 323

Morrice, D.J., Kenyon, A.S., Beckett, C.J., 2001. Optimizing operations in 3-D land seismic surveys Geophysics, 66 (6): 1818-1825.

Nikitas, P., Pappa-Louisi, A., 2000. Non-linear least-squares fitting with Microsoft Excel Solver and related routines in HPLC modeling of retention I. -Considerations of the problems of the method, Chromatographia, 52 (7-8): 477-486.

Nikitas, P., Pappa-Louisi, A., 2001. On the equations describing chromatographic peaks and the problem of the deconvolution of overlapped peaks, J. Chromatography A, 912 (1): 13-29.

Okennedy R., Camplisson, S., Patching, J.W., 1994. Microsoft (r) Excel macros for analyzing plasmid instability and their application to recombinant strains of saccharomyces-cerevisiae, Binary-Computing In Microbiology, 6 (6): 204-216.

Patton, R., Chen, J., Nielsen S., 1995. Model-based methods for fault diagnosis: Some guidelines, Transactions of the Institute of Measurement and Control, 17 (2), 73

Piertte, M.A., Kinney S.K., Haves P., 2001. Analysis of an information monitoring and diagnostic system to improve building operations, Energy and Buildings, 33 (2001) 783-791.

Reddy, T. A. and Claridge, D. E., 1994. Using synthetic data to evaluate multiple regression and principal component analyses for statistical modeling of daily building energy consumption, Energy and Buildings, Vol 21, pp. 35-44.

Reddy, T. A., Kissock, K. and Claridge, D. E., "Uncertainty Analysis in Estimating Building Energy Retrofit Savings in the LoanSTAR Program," Proceedings of the ACEEE 1992 Summer Study on Energy Efficiency in Buildings, Volume 3, American Council for an Energy Efficient Economy, Washington, D.C., pp. 225-237, 1992.

Salsbury, T. I., Diamond, R. C., 2001. Fault detection in HVAC systems using model-based feedforward control, Energy and Buildings 33: 403-415.

Sorooshian, S., 1981. Parameter-estimation of rainfall - runoff models with heteroscedastic streamflow errors - the non-informative data case, J. Hydrol., 52 (1-2): 127-138.

Sorooshian, S., Dracup, J.A., 1980. Stochastic parameter-estimation procedures for hydrologic rainfall-runoff models - correlated and heteroscedastic error cases, Water Resources Res.,16 (2): 430-442.

Sorooshian, S., Duan, Q.Y., Gupta, V.K., 1993. Calibration of rainfall-runoff models - application of global optimization to the Sacramento soil-moisture accounting model, Water Resources Res., 29 (4): 1185-1194.

Sorooshian, S., Gupta, V.K. Fulton, JL., 1983. Evaluation of maximum-likelihood parameter-estimation techniques for conceptual rainfall-runoff models - influence of calibration data variability and length on model credibility, Water Resources Res., 19 (1): 251-259.

Sorooshian, S., Gupta, V.K., 1983. Automatic calibration of conceptual rainfall-runoff models - the question of parameter observability and uniqueness, Water Resources Res., 19 (1): 260-268.

Subbarao, K., Burch, J., Hancock, C.E., Lekov, A., Balcomb, J.D., 1990. Measuring the energy performance of buildings through short-term tests, Proceedings of the ACEEE 1990 Summer Study on Energy Efficiency in Buildings, 10, 245-252.

Thiriez, H., 2001. Improved OR education through the use of spreadsheet models, European J. Operational Research, 135 (3): 461-476.

Walsh, S., Diamond, D., 1995. Nonlinear curve-fitting using Microsoft Excel Solver, Talanta, 42 (4): 561-572.

APPENDIX A

Table A-1. Assigned and detected fault parameters with 1% artificial noise.

1% Artificial Fault	Assigned Fault						Detected Fault					
	Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
One Variable Fault	1	45	73	1.2	10	2597106.7	1	44.9	73.1	1.19	10.1	5723.3
	2	55	78	1.2	10	1797997.6	2	54.8	78.1	1.18	10.1	5735.8
	3	55	73	0.4	10	1384965.4	3	55.2	73.0	0.40	10.0	5848.6
	4	55	73	1.2	30	1031475.9	4	55.0	73.0	1.20	30.1	5719.6

1% Artificial Fault	Assigned Fault						Detected Fault					
	Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
Two Variable Fault	5	45	68	1.2	10	1821707.5	5	44.9	68.1	1.19	10.1	5724.9
	6	65	68	1.2	10	1506124.0	6	65.1	68.1	1.20	10.0	5851.2
	7	45	73	0.4	10	1097413.9	7	45.1	73.1	0.40	10.0	5766.4
	8	65	73	0.4	10	1700423.0	8	65.9	72.9	0.46	8.9	5693.8
	9	45	73	1.2	3	2638741.9	9	44.7	73.1	1.18	3.0	5724.3
	10	65	73	1.2	30	528193.8	10	65.1	73.0	1.22	29.7	5675.7
	11	55	68	0.4	10	1567411.9	11	55.1	68.1	0.40	10.0	5836.5
	12	55	78	0.4	10	1209007.4	12	55.0	78.1	0.40	10.1	5816.7
	13	55	68	1.2	3	997006.9	13	54.8	68.1	1.17	3.1	5720.1
	14	55	78	1.2	30	1684638.0	14	55.0	78.0	1.20	30.1	5719.6
	15	55	73	0.4	3	1453220.9	15	53.2	73.2	0.36	3.3	5825.0
	16	55	73	0.4	30	1202213.6	16	55.0	73.0	0.40	30.0	5866.4

1% Artificial Fault	Assigned Fault						Detected Fault					
	Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
Three Variable Fault	17	45	68	0.4	10	1244871.7	17	45.3	68.0	0.41	9.9	5854.8
	18	65	78	0.4	10	1561815.3	18	65.9	77.8	0.44	9.3	5525.1
	19	45	68	1.2	3	1862536.2	19	44.8	68.1	1.19	3.0	5722.9
	20	65	78	1.2	30	5961.8	20	65.1	77.9	1.21	29.7	5694.5
	21	55	68	0.4	3	1635691.0	21	53.3	68.1	0.35	3.4	5812.1
	22	55	78	0.4	30	1021032.6	22	55.0	78.0	0.40	30.1	5808.8
	23	45	73	0.4	30	856883.7	23	45.0	73.1	0.40	30.1	5754.9
	24	65	73	0.4	3	1737258.4	24	67.1	73.0	0.55	2.3	5707.2
	25	65	68	1.2	3	1694783.7	25	65.1	68.1	1.20	3.0	5859.4
	26	45	78	1.2	30	3431439.7	26	45.0	78.0	1.20	30.0	5723.0

1% Artificial Fault	Assigned Fault						Detected Fault					
	Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
Four Variable Fault	27	65	68	0.4	3	1872289.7	27	66.1	68.1	0.63	2.0	5796.5
	28	45	78	0.4	30	741068.2	28	45.0	78.1	0.40	30.1	5772.3
	29	65	78	0.4	3	1598727.3	29	67.8	77.8	0.52	2.5	5522.7
	30	65	78	0.4	30	1416510.5	30	65.3	77.9	0.41	29.2	5621.5

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

Table A-2. Assigned and detected fault parameters with 3% artificial noise.

3% Artificial Fault	Assigned Fault						Detected Fault					
	Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
One Variable Fault	1	45	73	1.2	10	2594632.8	1	44.8	73.2	1.18	10.1	17245.4
	2	55	78	1.2	10	1795664.1	2	54.7	78.2	1.17	10.2	17235.7
	3	55	73	0.4	10	1387089.9	3	55.5	73.0	0.41	9.8	17573.2
	4	55	73	1.2	30	1029060.4	4	54.9	73.1	1.19	30.3	17234.8
3% Artificial Fault	Assigned Fault						Detected Fault					
	Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
Two Variable Fault	5	45	68	1.2	10	1819305.5	5	44.8	68.2	1.18	10.2	17245.4
	6	65	68	1.2	10	1508416.7	6	65.2	68.3	1.20	10.0	17553.5
	7	45	73	0.4	10	1099158.8	7	45.2	73.2	0.40	10.1	17389.6
	8	65	73	0.4	10	1702585.3	8	67.5	72.8	0.62	7.0	17081.7
	9	45	73	1.2	3	2636398.9	9	44.6	73.2	1.17	3.1	17246.3
	10	65	73	1.2	30	530948.1	10	65.2	72.9	1.25	29.0	17123.4
	11	55	68	0.4	10	1569564.4	11	55.3	68.1	0.41	9.9	17550.5
	12	55	78	0.4	10	1211027.3	12	54.9	78.2	0.40	10.2	17449.8
	13	55	68	1.2	3	997777.4	13	52.9	68.5	1.00	3.5	16845.3
	14	55	78	1.2	30	1681937.2	14	54.9	78.1	1.19	30.2	17234.8
	15	55	73	0.4	3	1455328.5	15	52.7	73.2	0.35	3.4	17459.5
	16	55	73	0.4	30	1204390.9	16	55.1	73.0	0.40	29.9	17599.2
3% Artificial Fault	Assigned Fault						Detected Fault					
	Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
Three Variable Fault	17	45	68	0.4	10	1246825.5	17	45.9	67.9	0.42	9.7	17575.4
	18	65	78	0.4	10	1564032.4	18	67.6	77.3	0.55	8.0	16576.2
	19	45	68	1.2	3	1860313.8	19	44.3	68.3	1.15	3.1	17245.9
	20	65	78	1.2	30	17885.3	20	65.2	77.8	1.25	29.1	17047.4
	21	55	68	0.4	3	1637832.2	21	53.2	68.1	0.35	3.4	17398.7
	22	55	78	0.4	30	1023132.8	22	54.9	78.1	0.40	30.3	17426.4
	23	45	73	0.4	30	858551.5	23	45.0	73.2	0.40	30.2	17364.4
	24	65	73	0.4	3	1739421.5	24	68.3	73.0	0.69	2.0	17296.7
	25	65	68	1.2	3	1696940.3	25	65.2	68.3	1.20	3.1	17578.2
	26	45	78	1.2	30	3428700.0	26	44.9	78.1	1.20	30.1	17245.2
3% Artificial Fault	Assigned Fault						Detected Fault					
	Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
Four Variable Fault	27	65	68	0.4	3	1874432.9	27	66.2	68.1	0.64	2.0	17610.6
	28	45	78	0.4	30	742194.9	28	44.9	78.2	0.40	30.2	17316.9
	29	65	78	0.4	3	1600939.0	29	68.6	77.7	0.58	2.4	16844.2
	30	65	78	0.4	30	1418893.1	30	65.8	77.6	0.44	27.5	16912.6

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

* Circled values are unacceptable detection values.

Table A-3. Assigned and detected fault parameters with 6% artificial noise.

6% Artificial Fault	Assigned Fault						Detected Fault					
	Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
One Variable Fault	1	45	73	1.2	10	2591026.3	1	44.6	73.4	1.17	10.3	34559.8
	2	55	78	1.2	10	1792316.6	2	52.6	79.1	1.04	11.2	33984.2
	3	55	73	0.4	10	1390464.7	3	56.1	72.9	0.43	9.5	35162.9
	4	55	73	1.2	30	1025746.0	4	54.8	73.2	1.18	30.6	34538.9

6% Artificial Fault	Assigned Fault						Detected Fault					
	Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
Two Variable Fault	5	45	68	1.2	10	1815865.5	5	44.6	68.3	1.17	10.3	34559.8
	6	65	68	1.2	10	1512026.6	6	65.4	68.6	1.20	10.1	35106.9
	7	45	73	0.4	10	1102023.9	7	48.0	72.9	0.45	9.2	34634.9
	8	65	73	0.4	10	1705982.8	8	68.6	72.8	0.80	5.6	34235.8
	9	45	73	1.2	3	2632988.2	9	47.7	73.0	1.33	2.8	34406.4
	10	65	73	1.2	30	535550.7	10	65.4	72.9	1.30	28.0	34297.0
	11	55	68	0.4	10	1572957.9	11	55.6	68.2	0.42	9.7	35122.7
	12	55	78	0.4	10	1214277.5	12	54.9	78.3	0.39	10.3	34899.0
	13	55	68	1.2	3	999267.8	13	51.0	69.0	0.86	4.0	33769.3
	14	55	78	1.2	30	1678043.9	14	54.8	78.2	1.18	30.4	34538.9
	15	55	73	0.4	3	1458671.2	15	52.6	73.2	0.35	3.5	34696.8
	16	55	73	0.4	30	1207870.4	16	55.2	73.0	0.41	29.8	35198.3

* The dimmed cells are assigned and detected fault parameters.

6% Artificial Fault	Assigned Fault						Detected Fault					
	Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
Three Variable Fault	17	45	68	0.4	10	1249966.2	17	48.0	67.6	0.47	8.8	34794.1
	18	65	78	0.4	10	1567525.0	18	68.6	77.0	0.64	7.1	33307.2
	19	45	68	1.2	3	1857141.9	19	47.7	68.0	1.36	2.7	34404.8
	20	65	78	1.2	30	35770.6	20	65.5	77.7	1.29	28.2	34086.5
	21	55	68	0.4	3	1641203.2	21	53.0	67.9	0.35	3.5	34814.4
	22	55	78	0.4	30	1026534.7	22	54.8	78.3	0.39	30.5	34852.7
	23	45	73	0.4	30	861356.6	23	45.0	73.3	0.40	30.3	34786.2
	24	65	73	0.4	3	1742818.1	24	68.6	73.1	0.72	2.0	34890.5
	25	65	68	1.2	3	1700328.9	25	65.5	68.6	1.20	3.1	35150.8
	26	45	78	1.2	30	3424666.8	26	44.9	78.2	1.19	30.2	34559.8

6% Artificial Fault	Assigned Fault						Detected Fault					
	Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
Four Variable Fault	27	65	68	0.4	3	1877789.6	27	66.4	68.2	0.67	2.0	35349.3
	28	45	78	0.4	30	744247.0	28	44.8	78.3	0.39	30.5	34633.8
	29	65	78	0.4	3	1604420.7	29	68.6	77.6	0.59	2.5	34264.8
	30	65	78	0.4	30	1422649.3	30	66.5	77.3	0.50	25.1	33854.6

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

Table A-4. Assigned and detected fault parameters with 10% artificial noise.

10% Artificial Fault	Assigned Fault Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Detected Fault 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 Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Detected Fault 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 Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Detected Fault 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 Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Detected Fault 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.

APPENDIX B

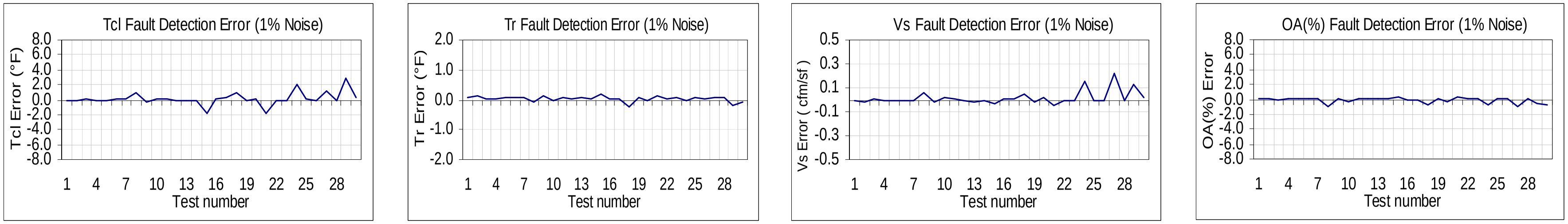

Figure B-1. Error between assigned and detected fault parameters with 1% artificial noise.

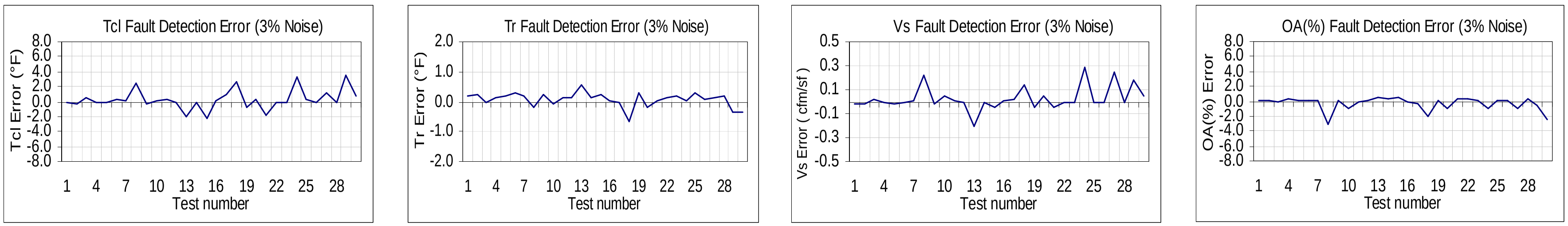

Figure B-2. Error between assigned and detected fault parameters with 3% artificial noise.

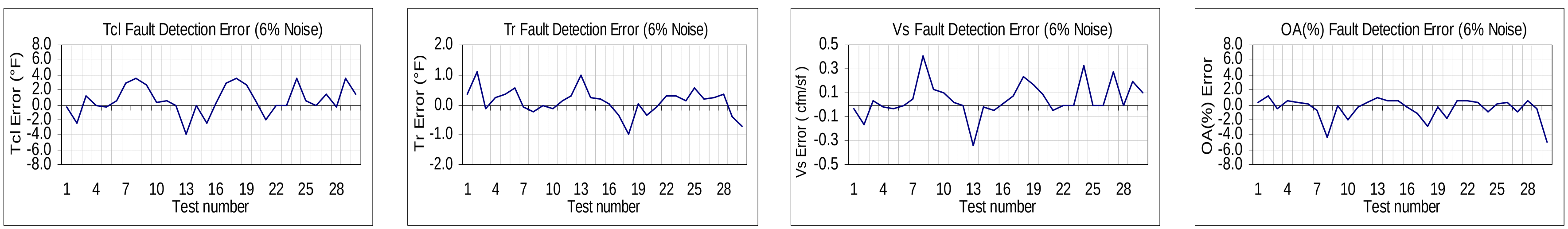

Figure B-3. Error between assigned and detected fault parameters with 6% artificial noise.

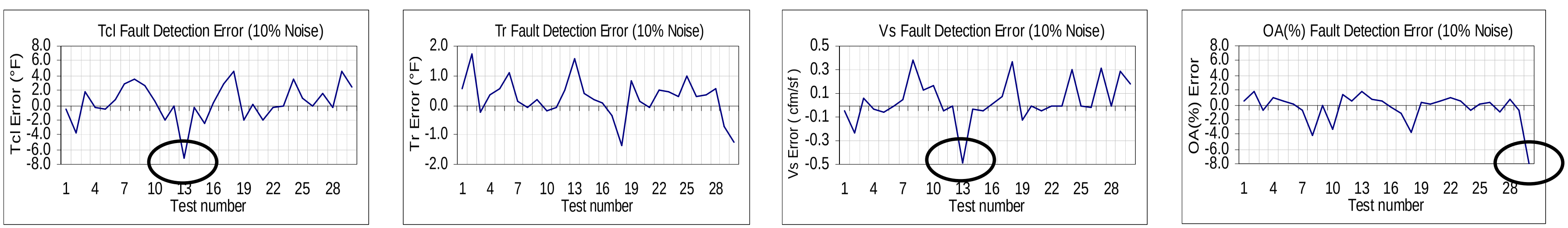

Figure B-4. Error between assigned and detected fault parameters with 10% artificial noise.

* Circled values are unacceptable detection values.