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

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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 approach¹ 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 $\pm 5^{\circ}$ F for Tcl. $\pm 2^{\circ}$ F for Tr, ± 0.4 cfm/sf for Vs, and $\pm 5\%$ for OA(%). If the acceptable errors for each parameter are reduced to $\pm 2.5^{\circ}$ F for Tcl, $\pm 1^{\circ}$ 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

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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 =

$$\begin{aligned}
\underbrace{\sum_{i=1}^{n} \sqrt{(CHW_{sim} - CHW_{mea})^{2}}}_{i=1} \\
\underbrace{\sum_{i=1}^{n} \sqrt{(HW_{sim} - HW_{mea})^{2}}}_{i=1} \\
\underbrace{\sum_{i=1}^{n} \sqrt{(HW_{sim} - HW_{mea})^{2}}}_{n-1}
\end{aligned}$$

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 facade areas of the building) have a U-value of 1.1 Btu/h-°F-SF. The remaining exterior sidewall area is 30,940 SF and the roof area is 24,000 SF. The wall Uvalue is 0.1 Btu/h-°F-SF and the roof U-value is 0.05 Btu/h-°F-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 °F 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 detection the fault 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 synthetic corresponding to the 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 $\pm 5^{\circ}$ F for Tcl. $\pm 2^{\circ}$ F for Tr, ± 0.4 cfm/sf for Vs, and $\pm 5\%$ for OA(%). If the acceptable errors for each parameter are reduced to $\pm 2.5^{\circ}$ F for Tcl, $\pm 1^{\circ}$ 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 $\pm 10^{\circ}$ F and $\pm 10^{\circ}$ F from the original setting of Tcl, $\pm 5^{\circ}$ F from the original Tr setpoint, ± 0.8 cfm/ft² from the original Vs, and $\pm 20\%$ and $\pm 7\%$ 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 procedures optimization 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.

			Tc			Tr		Sup	oply air		OA(%	6)	
		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	
	Average	45.4	66.6	54.2	68.3	78.0	73.1	0.5	1.2	2.9	29.6	9.5	
Detected	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	
TOIETATICE	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 to # of	olerance / test	1/120			0/120			1/120		1/120			
Mean Bia	as Error		0.4			0.1			0.0		-0.3		

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

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 $\pm 5^{\circ}F$ for Tcl, $\pm 2^{\circ}F$ for Tr, ± 0.4 cfm/sf for Vs, and $\pm 5\%$ for OA(%). If the acceptable fault detection criteria are tightened to $\pm 2.5^{\circ}$ F for Tcl, $\pm 1^{\circ}$ F for Tr, ± 0.2 cfm/sf for Vs, and $\pm 2.5\%$ 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.

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APPENDIX A

Table A 1	Accigned and	detected foult	nonomotors with	10/	artificial naica
Table A-1. F	Assigned and	uelecteu laun	parameters with	1 70	artificial noise.

1%			Assig	ned F	ault				Dete	cted F	ault	
Artificial Fault	Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
One	1	45	73	1.2	10	2597106.7	1	44.9	73.1	1.19	10.1	5723.3
Variable	2	55	78	1.2	10	1797997.6	2	54.8	78.1	1.18	10.1	5735.8
Fault	3	55	73	0.4	10	1384965.4	3	55.2	73.0	0.40	10.0	5848.6
1 dan	4	55	73	1.2	30	1031475.9	4	55.0	73.0	1.20	30.1	5719.6
1%			Assig	ned F	ault				Dete	cted F	ault	
Artificial Fault	Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
	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
Two	9	45	73	1.2	3	2638741.9	9	44.7	73.1	1.18	3.0	5724.3
Variable	10	65	73	1.2	30	528193.8	10	65.1	73.0	1.22	29.7	5675.7
Fault	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%			Assig	ned F	ault				Dete	cted F	ault	
Artificial Fault	Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
	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	
Three	20	65	78	1.2	30	E004 0	10				0.0	5722.9
Variable	21				00	5901.8	20	65.1	77.9	1.21	29.7	5722.9 5694.5
Fault		55	68	0.4	3	1635691.0	20 21	<mark>65.1</mark> 53.3	77.9 68.1	1.21 0.35	29.7 3.4	5722.9 5694.5 5812.1
	22	55 55	68 78	0.4 0.4	3 30	1635691.0 1021032.6	20 21 22	<mark>65.1</mark> 53.3 55.0	77.9 68.1 78.0	1.21 0.35 0.40	29.7 3.4 30.1	5722.9 5694.5 5812.1 5808.8
	22 23	55 55 45	68 78 73	0.4 0.4 0.4	30 30	5961.8 1635691.0 1021032.6 856883.7	20 21 22 23	65.1 53.3 55.0 45.0	77.9 68.1 78.0 73.1	1.21 0.35 0.40 0.40	29.7 3.4 30.1 30.1	5722.9 5694.5 5812.1 5808.8 5754.9
	22 23 24	55 55 45 65	68 78 73 73	0.4 0.4 0.4	30 30 30 30	5961.8 1635691.0 1021032.6 856883.7 1737258.4	20 21 22 23 24	65.1 53.3 55.0 45.0 67.1	77.9 68.1 78.0 73.1 73.0	1.21 0.35 0.40 0.40 0.55	29.7 3.4 30.1 30.1 2.3	5722.9 5694.5 5812.1 5808.8 5754.9 5707.2
	22 23 24 25	55 55 45 65 65	68 78 73 73 68	0.4 0.4 0.4 1.2	3 30 30 30 3 3	5961.8 1635691.0 1021032.6 856883.7 1737258.4 1694783.7	20 21 22 23 24 25	65.1 53.3 55.0 45.0 67.1 65.1	77.9 68.1 78.0 73.1 73.0 68.1	1.21 0.35 0.40 0.40 0.55 1.20	29.7 3.4 30.1 30.1 2.3 3.0	5722.9 5694.5 5812.1 5808.8 5754.9 5707.2 5859.4
	22 23 24 25 26	55 55 45 65 65 45	68 78 73 73 68 78	0.4 0.4 0.4 1.2 1.2	30 30 30 3 3 3 30	1635691.0 1021032.6 856883.7 1737258.4 1694783.7 3431439.7	20 21 22 23 24 25 26	65.1 53.3 55.0 45.0 67.1 65.1 45.0	77.9 68.1 78.0 73.1 73.0 68.1 78.0	1.21 0.35 0.40 0.40 0.55 1.20 1.20	29.7 3.4 30.1 30.1 2.3 3.0 30.0	5722.9 5694.5 5812.1 5808.8 5754.9 5707.2 5859.4 5723.0
	22 23 24 25 26	55 55 45 65 65 45	68 78 73 73 68 78	0.4 0.4 0.4 1.2 1.2	30 30 30 30 30 30	1635691.0 1021032.6 856883.7 1737258.4 1694783.7 3431439.7	10 20 21 22 23 24 25 26	65.1 53.3 55.0 45.0 67.1 65.1 45.0	77.9 68.1 78.0 73.1 73.0 68.1 78.0	1.21 0.35 0.40 0.40 0.55 1.20 1.20	29.7 3.4 30.1 30.1 2.3 3.0 30.0	5722.9 5694.5 5812.1 5808.8 5754.9 5707.2 5859.4 5723.0
1%	22 23 24 25 26	55 55 45 65 65 45	68 78 73 73 68 78 Assig	0.4 0.4 0.4 1.2 1.2	3 30 30 30 30 30	5961.8 1635691.0 1021032.6 856883.7 1737258.4 1694783.7 3431439.7	10 20 21 22 23 24 25 26	65.1 53.3 55.0 45.0 67.1 65.1 45.0	77.9 68.1 78.0 73.1 73.0 68.1 78.0 Dete	1.21 0.35 0.40 0.55 1.20 1.20	29.7 3.4 30.1 30.1 2.3 3.0 30.0	5722.9 5694.5 5812.1 5808.8 5754.9 5707.2 5859.4 5723.0
1% Artificial Fault	22 23 24 25 26 Data No.	55 55 45 65 65 45 Tcl	68 78 73 73 68 78 78 Assiç	0.4 0.4 0.4 1.2 1.2 gned F	3 30 30 30 30 30 30 -ault	1635691.0 1021032.6 856883.7 1737258.4 1694783.7 3431439.7 RMSE	20 21 22 23 24 25 26 Data No.	65.1 53.3 55.0 45.0 67.1 65.1 45.0	77.9 68.1 78.0 73.1 73.0 68.1 78.0 Dete Tr	1.21 0.35 0.40 0.55 1.20 1.20 t.20	29.7 3.4 30.1 30.1 2.3 3.0 30.0 30.0	5722.9 5694.5 5812.1 5808.8 5754.9 5707.2 5859.4 5723.0 RMSE
1% Artificial Fault	22 23 24 25 26 Data No. 27	55 55 45 65 65 45 Tcl	68 78 73 73 68 78 Assiç Tr 68	0.4 0.4 0.4 1.2 1.2 1.2 yned F Vs 0.4	3 30 30 30 30 30 30 - ault OA(%)	3961.8 1635691.0 1021032.6 856883.7 1737258.4 1694783.7 3431439.7 RMSE 1872289.7	20 21 22 23 24 25 26 Data No. 27	65.1 53.3 55.0 45.0 67.1 65.1 45.0 Tcl 66.1	77.9 68.1 78.0 73.1 73.0 68.1 78.0 Dete Tr 68.1	1.21 0.35 0.40 0.55 1.20 1.20 cted F Vs 0.63	29.7 3.4 30.1 2.3 3.0 30.0 30.0	5722.9 5694.5 5812.1 5808.8 5754.9 5707.2 5859.4 5723.0 RMSE 5796.5
1% Artificial Fault Four Variable	22 23 24 25 26 Data No. 27 28	55 55 45 65 65 45 Tcl 65 45	68 78 73 73 68 78 Assiç Tr 68 78	0.4 0.4 0.4 1.2 1.2 1.2 yned F Vs 0.4 0.4	ault OA(%) 30 30 30 30 30	3961.8 1635691.0 1021032.6 856883.7 1737258.4 1694783.7 3431439.7 RMSE 1872289.7 741068.2	20 21 22 23 24 25 26 Data No. 27 28	65.1 53.3 55.0 67.1 65.1 45.0 Tcl 66.1 45.0	77.9 68.1 73.0 68.1 78.0 68.1 78.0 Dete Tr 68.1 78.1	1.21 0.35 0.40 0.55 1.20 1.20 t.20 vs 0.63 0.40	29.7 3.4 30.1 30.1 2.3 3.0 30.0 30.0	5722.9 5694.5 5812.1 5808.8 5754.9 5707.2 5859.4 5723.0 RMSE 5796.5 5772.3
1% Artificial Fault Four Variable	22 23 24 25 26 Data No. 27 28 29	55 55 45 65 65 45 Tcl 65 45 65	68 73 73 68 78 78 Assig Tr 68 78 78 78	0.4 0.4 0.4 1.2 1.2 1.2 Vs 0.4 0.4 0.4	ault OA(%) 30 30 30 30 30 30 30 30 30	3961.8 1635691.0 1021032.6 856883.7 1737258.4 1694783.7 3431439.7 RMSE 1872289.7 741068.2 1598727.3	20 21 22 23 24 25 26 Data No. 27 28 29	65.1 53.3 55.0 67.1 65.1 45.0 Tcl 66.1 45.0 67.8	77.9 68.1 78.0 73.1 73.0 68.1 78.0 Dete Tr 68.1 78.1 78.1 77.8	1.21 0.35 0.40 0.55 1.20 1.20 1.20 cted F Vs 0.63 0.40 0.52	29.7 3.4 30.1 2.3 3.0 30.0 30.0 CA(%) 2.0 30.1 2.5	5722.9 5694.5 5812.1 5808.8 5754.9 5707.2 5859.4 5723.0 RMSE 5796.5 5772.3 5522.7

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

3%			Assig	ned F	ault				Dete	cted F	ault	
Artificial Fault	Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
One	1	45	73	1.2	10	2594632.8	1	44.8	73.2	1.18	10.1	17245.4
Variable	2	55	78	1.2	10	1795664.1	2	54.7	78.2	1.17	10.2	17235.7
Fault	3	55	73	0.4	10	1387089.9	3	55.5	73.0	0.41	9.8	17573.2
T aut	4	55	73	1.2	30	1029060.4	4	54.9	73.1	1.19	30.3	17234.8
3%			Assig	ned F	ault				Dete	cted F	ault	
Artificial Fault	Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
	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
Two	9	45	73	1.2	3	2636398.9	9	44.6	73.2	1.17	3.1	17246.3
Variable	10	65	73	1.2	30	530948.1	10	65.2	72.9	1.25	29.0	17123.4
Fault	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%			Assig	ned F	ault				Dete	cted F	ault	
Artificial Fault	Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
	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
Three	20	65	78	1.2	30	17885.3	20	65.2	77.8	1.25	29.1	17047.4
Variable	21	55	68	0.4	3	1637832.2	21	53.2	68.1	0.35	3.4	17398.7
Fault	22	55	78	0.4	30	1023132.8	22	54.9	78.1	0.40	30.3	17426.4
i dun	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
00/			Accio	ined F	ault				Dete	cted F	ault	
3%			Assig	,								
3% Artificial Fault	Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
3% Artificial Fault	Data No. 27	Tcl 65	Tr	Vs 0.4	OA(%) 3	RMSE 1874432.9	Data No. 27	Tcl 66.2	Tr 68.1	Vs 0.64	OA(%) 2.0	RMSE 17610.6
3% Artificial Fault Four	Data No. 27 28	Tcl 65 45	Tr 68 78	Vs 0.4 0.4	OA(%) 3 30	RMSE 1874432.9 742194.9	Data No. 27 28	Tcl 66.2 44.9	Tr 68.1 78.2	Vs 0.64 0.40	OA(%) 2.0 30.2	RMSE 17610.6 17316.9
3% Artificial Fault Four Variable	Data No. 27 28 29	Tcl 65 45 65	Tr 68 78 78	Vs 0.4 0.4 0.4	OA(%) 3 30 30 3	RMSE 1874432.9 742194.9 1600939.0	Data No. 27 28 29	Tcl 66.2 44.9 68.6	Tr 68.1 78.2 77.7	Vs 0.64 0.40 0.58	OA(%) 2.0 30.2 2.4	RMSE 17610.6 17316.9 16844.2

Table A-2. Assigned and detected fault parame	eters with 3% artificial	noise.
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* The dimmed cells are assigned or detected fault parameters, others are original parameters and it's detected values.

6%			Assig	gned F	ault				Dete	cted F	ault	
Artificial Fault	Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
One	1	45	73	1.2	10	2591026.3	1	44.6	73.4	1.17	10.3	34559.8
Variable	2	55	78	1.2	10	1792316.6	2	52.6	79.1	1.04	11.2	33984.2
Fault	3	55	73	0.4	10	1390464.7	3	56.1	72.9	0.43	9.5	35162.9
1 dan	4	55	73	1.2	30	1025746.0	4	54.8	73.2	1.18	30.6	34538.9
6%			Assig	ned F	ault				Dete	cted F	ault	
Artificial Fault	Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
	5	45	68	1.2	10	1815865.5	5	44.6	68.3	1.17	10.3	34559.8
* T	he 6 im	med c 615 5	are as big i	ned 1 an 2	detec 1Q	f 1.5.12026.6 s	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
Two	9	45	73	1.2	3	2632988.2	9	47.7	73.0	1.33	2.8	34406.4
Variable	10	65	73	1.2	30	535550.7	10	65.4	72.9	1.30	28.0	34297.0
Fault	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		70									
	10	55	73	0.4	30	1207870.4	16	55.2	73.0	0.41	29.8	35198.3
	10	55	73	0.4	30	1207870.4	16	55.2	73.0	0.41	29.8	35198.3
6%	10	55	73 Assig	0.4 gned F	ault	1207870.4	16	55.2	73.0 Dete	0.41 cted F	29.8 ault	35198.3
6% Artificial Fault	Data No.	Tcl	Assig Tr	oned F Vs	-ault OA(%)	1207870.4 RMSE	16 Data No.	55.2 Tcl	73.0 Dete	0.41 cted F Vs	29.8 ault	35198.3 RMSE
6% Artificial Fault	Data No. 17	55 Tcl 45	Assig Tr 68	0.4 gned F Vs 0.4	30 Fault OA(%) 10	1207870.4 RMSE 1249966.2	16 Data No. 17	55.2 Tcl 48.0	73.0 Dete Tr 67.6	0.41 cted F Vs 0.47	29.8 ault OA(%) 8.8	35198.3 RMSE 34794.1
6% Artificial Fault	Data No. 17 18	55 Tcl 45 65	Assig Tr 68 78	0.4 gned F Vs 0.4 0.4	30 Fault OA(%) 10 10	RMSE 1249966.2 1567525.0	16 Data No. 17 18	55.2 Tcl 48.0 68.6	73.0 Dete Tr 67.6 77.0	0.41 cted F Vs 0.47 0.64	29.8 ault OA(%) 8.8 7.1	RMSE 34794.1 33307.2
6% Artificial Fault	Data No. 17 18 19	55 Tcl 45 65 45	73 Assig Tr 68 78 68	0.4 gned F Vs 0.4 0.4 1.2	30 Fault OA(%) 10 10 3	RMSE 1249966.2 1567525.0 1857141.9	16 Data No. 17 18 19	Tcl 48.0 68.6 47.7	73.0 Dete Tr 67.6 77.0 68.0	0.41 cted F Vs 0.47 0.64 1.36	29.8 Fault OA(%) 8.8 7.1 2.7	RMSE 34794.1 33307.2 34404.8
6% Artificial Fault Three	Data No. 17 18 19 20	55 Tcl 45 65 45 65	Assiç Tr 68 78 68 78 78	0.4 gned F Vs 0.4 1.2 1.2	30 Fault OA(%) 10 10 30	RMSE 1249966.2 1567525.0 1857141.9 35770.6	16 Data No. 17 18 19 20	55.2 Tcl 48.0 68.6 47.7 65.5	73.0 Dete Tr 67.6 77.0 68.0 77.7	0.41 Cted F Vs 0.47 0.64 1.36 1.29	29.8 Fault OA(%) 8.8 7.1 2.7 28.2	RMSE 34794.1 33307.2 34404.8 34086.5
6% Artificial Fault Three Variable	Data No. 17 18 19 20 21	55 Tcl 45 65 45 65 55	73 Assig Tr 68 78 68 78 68 78 68	0.4 gned F Vs 0.4 0.4 1.2 1.2 0.4	30 Fault OA(%) 10 10 30 30	RMSE 1249966.2 1567525.0 1857141.9 35770.6 1641203.2	16 Data No. 17 18 19 20 21	Tcl 48.0 68.6 47.7 65.5 53.0	73.0 Dete Tr 67.6 77.0 68.0 77.7 67.9	0.41 cted F Vs 0.47 0.64 1.36 1.29 0.35	29.8 Fault OA(%) 8.8 7.1 2.7 28.2 3.5	RMSE 34794.1 33307.2 34404.8 34086.5 34814.4
6% Artificial Fault Three Variable Fault	Data No. 17 18 19 20 21 22	Tcl 45 65 65 55 55	73 Assig Tr 68 78 68 78 68 78 68 78 68 78 68 78 68 78	0.4 gned F Vs 0.4 0.4 1.2 1.2 0.4 0.4	30 Fault OA(%) 10 10 30 30 30 30	RMSE 1249966.2 1567525.0 1857141.9 35770.6 1641203.2 1026534.7	16 Data No. 17 18 19 20 21 22	Tcl 48.0 68.6 47.7 65.5 53.0 54.8	73.0 Dete Tr 67.6 77.0 68.0 77.7 67.9 78.3	0.41 cted F Vs 0.47 0.64 1.36 1.29 0.35 0.39	29.8 	RMSE 34794.1 33307.2 34404.8 34086.5 34814.4 34852.7
6% Artificial Fault Three Variable Fault	Data No. 17 18 19 20 21 22 23	55 Tcl 45 65 65 55 55 55 55	Assig Tr 68 78 68 78 68 78 68 78 68 78	0.4 gned F Vs 0.4 0.4 1.2 1.2 0.4 0.4	-ault OA(%) 10 10 30 30 30 30	RMSE 1249966.2 1567525.0 1857141.9 35770.6 1641203.2 1026534.7 861356.6	16 Data No. 17 18 19 20 21 22 23 23	Tcl 48.0 68.6 47.7 65.5 53.0 54.8 45.0	73.0 Dete Tr 67.6 77.0 68.0 77.7 67.9 78.3 73.3	0.41 Cted F Vs 0.47 0.64 1.36 1.29 0.35 0.39 0.39	29.8 ault OA(%) 8.8 7.1 2.7 28.2 3.5 30.5 30.5	RMSE 34794.1 33307.2 34404.8 34086.5 34814.4 34852.7 34786.2
6% Artificial Fault Three Variable Fault	Data No. 17 18 19 20 21 22 23 24	55 Tcl 45 65 65 55 55 55 45 65	73 Assiç Tr 68 78 68 78 68 78 68 73 73	0.4 gned F Vs 0.4 0.4 1.2 1.2 0.4 0.4 0.4 0.4	-ault OA(%) 10 10 30 30 30 30 30 30	1207870.4 RMSE 1249966.2 1567525.0 1857141.9 35770.6 1641203.2 1026534.7 861356.6 1742818.1	16 Data No. 17 18 19 20 21 22 23 24 24	Tcl 48.0 68.6 47.7 65.5 53.0 54.8 45.0 68.6	73.0 Dete Tr 67.6 77.0 68.0 77.7 67.9 78.3 73.3 73.3 73.3	0.41 cted F Vs 0.47 0.64 1.36 1.29 0.35 0.39 0.40 0.40 0.72	29.8 ault OA(%) 8.8 7.1 2.7 28.2 30.5 30.3 30.3 2.0	35198.3 RMSE 34794.1 33307.2 34404.8 34086.5 34814.4 34852.7 34786.2 34890.5
6% Artificial Fault Three Variable Fault	Data No. 17 18 19 20 21 22 23 24 25	Tcl 45 65 45 55 55 55 45 65 65	73 Assig Tr 68 78 68 78 68 78 68 78 68 78 68 78 68 78 68 78 68 73 73 68	0.4 gned F Vs 0.4 0.4 1.2 1.2 0.4 0.4 0.4 0.4 0.4	30 -ault OA(%) 10 10 30 30 30 30 30 30 30 30	1207870.4 RMSE 1249966.2 1567525.0 1857141.9 35770.6 1641203.2 1026534.7 861356.6 1742818.1 1700328.9	16 Data No. 17 18 19 20 21 22 23 24 25 24	Tcl 48.0 68.6 47.7 65.5 53.0 54.8 45.0 68.6 65.5	73.0 Dete Tr 67.6 77.0 68.0 77.7 67.9 78.3 73.3 73.1 68.6	0.41 Cted F Vs 0.47 0.64 1.36 1.29 0.35 0.39 0.40 0.72 1.20	29.8 ault OA(%) 8.8 7.1 2.7 28.2 3.5 30.5 30.3 2.0 3.1	RMSE 34794.1 33307.2 34404.8 34086.5 34814.4 34852.7 34852.7 34786.2 34890.5 35150.8
6% Artificial Fault Three Variable Fault	Data No. 17 18 19 20 21 22 23 24 25 26	55 Tcl 45 65 55 55 55 55 45 65 65 65 45	73 Assig Tr 68 78 68 78 68 78 68 78 68 78 68 78 68 78 68 73 68 73 68 78	0.4 gned F Vs 0.4 0.4 1.2 1.2 0.4 0.4 0.4 0.4 1.2 1.2	30 Fault OA(%) 10 10 10 30 30 30 30 30 30 30 30 30	1207870.4 RMSE 1249966.2 1567525.0 1857141.9 35770.6 1641203.2 1026534.7 861356.6 1742818.1 1700328.9 3424666.8	16 Data No. 17 18 19 20 21 22 23 24 25 26	Tcl 48.0 68.6 47.7 65.5 53.0 54.8 45.0 68.6 65.5 44.9	73.0 Dete Tr 67.6 77.0 68.0 77.7 67.9 78.3 73.3 73.1 68.6 78.2	0.41 Cted F Vs 0.47 0.64 1.36 1.29 0.35 0.39 0.40 0.72 1.20 1.19	29.8 ault OA(%) 8.8 7.1 2.7 28.2 3.5 30.5 30.3 2.0 3.1 30.2	RMSE 34794.1 33307.2 34404.8 34086.5 34814.4 34852.7 34786.2 34890.5 35150.8 35150.8 34559.8
6% Artificial Fault Three Variable Fault	Data No. 17 18 19 20 21 22 23 24 25 26	55 Tcl 45 65 55 55 55 55 65 65 45 65 45	73 Assig Tr 68 78 68 78 68 73 68 73 73 68 78 73 68 78	0.4 gned F Vs 0.4 0.4 1.2 1.2 0.4 0.4 0.4 0.4 1.2 1.2	30 -ault OA(%) 10 10 10 30 30 30 30 30 30 30 30 30 30 30	RMSE 1249966.2 1567525.0 1857141.9 35770.6 1641203.2 1026534.7 861356.6 1742818.1 1700328.9 3424666.8	16 Data No. 17 18 19 20 21 22 23 24 25 26	Tcl 48.0 68.6 47.7 65.5 53.0 54.8 45.0 68.6 65.5 44.9	73.0 Dete Tr 67.6 77.0 68.0 77.7 67.9 78.3 73.3 73.1 68.6 78.2	0.41 Cted F Vs 0.47 0.64 1.36 1.29 0.35 0.39 0.40 0.72 1.20 1.19	29.8 ault OA(%) 8.8 7.1 2.7 28.2 30.5 30.5 30.5 30.3 2.0 3.1 30.2	RMSE 34794.1 33307.2 34404.8 34086.5 34814.4 34852.7 34786.2 34786.2 34786.2 34786.2 34559.8
6% Artificial Fault Three Variable Fault	Data No. 17 18 19 20 21 22 23 24 25 26	55 Tcl 45 65 65 55 55 55 65 65 65 45	Assig Tr 68 78 68 78 68 78 68 73 73 68 73 68 78 78 73	0.4 gned F Vs 0.4 0.4 1.2 1.2 0.4 0.4 0.4 0.4 0.4 1.2 1.2 1.2	-ault OA(%) 10 10 30 30 30 30 30 30 30 30 30 30 5 30	1207870.4 RMSE 1249966.2 1567525.0 1857141.9 35770.6 1641203.2 1026534.7 861356.6 1742818.1 1700328.9 3424666.8	16 Data No. 17 18 19 20 21 22 23 24 25 26	Tcl 48.0 68.6 47.7 65.5 53.0 54.8 45.0 68.6 65.5 44.9	73.0 Dete Tr 67.6 77.0 68.0 77.7 67.9 78.3 73.3 73.1 68.6 78.2 Dete	0.41 cted F Vs 0.47 0.64 1.36 1.29 0.35 0.39 0.40 0.72 1.20 1.19 cted F	29.8 ault OA(%) 8.8 7.1 28.2 30.5 30.5 30.3 2.0 3.1 30.2 30.2	35198.3 RMSE 34794.1 33307.2 34404.8 34086.5 34814.4 34852.7 34786.2 34890.5 35150.8 34559.8
6% Artificial Fault Three Variable Fault 6% Artificial Fault	Data No. 17 18 19 20 21 22 23 24 25 26 Data No.	Tcl 45 65 45 55 55 55 65 65 45 45 7cl	73 Assig Tr 68 78 68 78 68 73 68 73 68 73 68 78 68 78 68 78 Assig Tr	0.4 gned F Vs 0.4 0.4 1.2 1.2 0.4 0.4 0.4 0.4 0.4 1.2 1.2 1.2 Spned F Vs	-ault OA(%) 10 10 30 30 30 30 30 30 30 30 -ault OA(%)	1207870.4 RMSE 1249966.2 1567525.0 1857141.9 35770.6 1641203.2 1026534.7 861356.6 1742818.1 1700328.9 3424666.8 RMSE	16 Data No. 17 18 19 20 21 22 23 24 25 26 Data No.	Tcl 48.0 68.6 47.7 65.5 53.0 54.8 45.0 68.6 65.5 44.9 Tcl	73.0 Dete Tr 67.6 77.0 68.0 77.7 67.9 78.3 73.3 73.1 68.6 78.2 Dete Tr	0.41 Cted F Vs 0.47 0.64 1.36 1.29 0.35 0.39 0.40 0.72 1.20 1.19 Cted F Vs	29.8 ault OA(%) 8.8 7.1 2.7 28.2 3.5 30.5 30.3 2.0 3.1 30.2 	RMSE 34794.1 33307.2 34404.8 34086.5 34814.4 34852.7 34852.7 34786.2 34890.5 35150.8 34559.8 RMSE
6% Artificial Fault Three Variable Fault 6% Artificial Fault	Data No. 17 18 19 20 21 22 23 24 25 26 26 Data No. 27	55 Tcl 45 65 55 55 55 55 65 65 65 65 45 7cl	Assig Tr 68 78 68 78 68 78 68 73 73 68 73 68 73 73 68 78 73 73 68 78 73 73 68 78 73 73 68 78 78 73 73 68 78 78 78 78 78 78 68 78 78 68 78 78 68 78 78 68 78 78 68 78 78 68 78 78 68 78 78 68 78 78 68 78 78 68 78 78 68 78 78 68 78 78 68 78 78 68 78 78 68 78 78 68 78 78 68 78 78 68 78 78 68 78 78 78 68 78 78 78 78 78 78 78 78 78 78 78 78 78	0.4 gned F Vs 0.4 0.4 1.2 1.2 0.4 0.4 0.4 0.4 1.2 1.2 gned F Vs 0.4	30 ault OA(%) 10 10 10 30 30 30 30 30 30 30 30 30 30 30 30 30	1207870.4 RMSE 1249966.2 1567525.0 1857141.9 35770.6 1641203.2 1026534.7 861356.6 1742818.1 1700328.9 3424666.8 RMSE 1877789.6	16 Data No. 17 18 19 20 21 22 23 24 25 26 26 Data No. 27	Tcl 48.0 68.6 47.7 65.5 53.0 54.8 45.0 68.6 65.5 44.9 Tcl 66.4	73.0 Dete Tr 67.6 77.0 68.0 77.7 67.9 78.3 73.3 73.1 68.6 78.2 Dete Tr C 68.2	0.41 Cted F Vs 0.47 0.64 1.36 1.29 0.35 0.39 0.40 0.72 1.20 1.20 1.19 Cted F Vs 0.67	29.8 ault OA(%) 8.8 7.1 2.7 28.2 30.5 30.5 30.3 2.0 3.1 30.2 30.2 30.2	RMSE 34794.1 33307.2 34404.8 34086.5 34814.4 34852.7 34786.2 34890.5 35150.8 35150.8 34559.8 RMSE 35349.3
6% Artificial Fault Three Variable Fault 6% Artificial Fault Four	Data No. 17 18 19 20 21 22 23 24 25 26 26 Data No. 27 28	Tcl 45 65 45 65 55 55 55 65 65 65 45 7cl 65 45	73 Assig Tr 68 78 68 78 68 73 68 73 68 73 68 78 68 78 68 78 68 78 68 78 68 78	0.4 gned F Vs 0.4 0.4 1.2 1.2 0.4 0.4 0.4 1.2 1.2 1.2 yned F Vs 0.4 0.4	-ault OA(%) 10 10 30 30 30 30 30 30 30 -ault OA(%) 30	1207870.4 RMSE 1249966.2 1567525.0 1857141.9 35770.6 1641203.2 1026534.7 861356.6 1742818.1 1700328.9 3424666.8 RMSE 1877789.6 744247.0	16 Data No. 17 18 19 20 21 22 23 24 25 26 26 Data No. 27 28	Tcl 48.0 68.6 47.7 65.5 53.0 54.8 45.0 68.6 65.5 44.9 Tcl 66.4 44.8	73.0 Dete Tr 67.6 77.0 68.0 77.7 67.9 78.3 73.3 73.1 68.6 78.2 Dete Tr 68.2 78.3	0.41 Cted F Vs 0.47 0.64 1.36 1.29 0.35 0.39 0.40 0.72 1.20 1.19 Cted F Vs 0.67 0.39	29.8 ault OA(%) 8.8 7.1 2.7 28.2 30.5 30.5 30.3 2.0 3.1 30.2 30.2 5 ault OA(%) 2.0 30.5	35198.3 RMSE 34794.1 33307.2 34404.8 34086.5 34814.4 34852.7 34786.2 34786.2 34786.2 34786.2 34786.2 34559.8 34559.8 34559.8 RMSE 35349.3 34633.8
6% Artificial Fault Three Variable Fault 6% Artificial Fault Four Variable	Data No. 17 18 19 20 21 22 23 24 25 26 Data No. 27 28 29	Tcl 45 65 45 65 55 55 65 65 65 45 65 45 7cl 55 65 65 65 65 65 65 65 65 65 65 65 65	Assiç Tr 68 78 68 78 68 78 73 68 73 68 78 78 78 78 78 78 78 78	0.4 gned F Vs 0.4 0.4 1.2 1.2 0.4 0.4 0.4 1.2 1.2 1.2 1.2 0.4 0.4 0.4 0.4 0.4 0.4 0.4 0.4 0.4	-ault OA(%) 10 10 30 30 30 30 30 30 30 30 30 30 30 30 30	1207870.4 RMSE 1249966.2 1567525.0 1857141.9 35770.6 1641203.2 1026534.7 861356.6 1742818.1 1700328.9 3424666.8 RMSE 1877789.6 744247.0 1604420.7	16 Data No. 17 18 19 20 21 22 23 24 25 26 26 Data No. 27 28 29	Tcl 48.0 68.6 47.7 65.5 53.0 54.8 45.0 68.6 65.5 44.9 Tcl 66.4 44.8 68.6	73.0 Dete Tr 67.6 77.0 68.0 77.7 67.9 78.3 73.3 73.3 73.1 68.6 78.2 Dete Tr 68.2 78.3 77.6	0.41 cted F Vs 0.47 0.64 1.36 1.29 0.35 0.39 0.40 0.72 1.20 1.19 cted F Vs 0.67 0.39 0.39 0.39 0.59	29.8 ault OA(%) 8.8 7.1 2.7 28.2 3.5 30.3 2.0 3.1 30.3 2.0 3.1 30.2 30.5 30.2 30.5 30.5 30.5 30.5 30.5 30.5 30.5 30.5	35198.3 RMSE 34794.1 33307.2 34404.8 34086.5 34814.4 34852.7 34786.2 34890.5 35150.8 34559.8 34559.8 34559.8 RMSE 35349.3 34633.8 34264.8

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

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

10%			Assig	ned F	ault				Dete	cted F	ault	
Artificial Fault	Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
One	1	45	73	1.2	10	2586413.8	1	44.4	73.6	1.15	10.4	57651.6
Variable	2	55	78	1.2	10	1788140.6	2	51.2	79.7	0.96	11.9	56451.7
Fault	3	55	73	0.4	10	1395312.3	3	56.8	72.7	0.46	9.2	58635.9
1 dan	4	55	73	1.2	30	1021912.8	4	54.7	73.4	1.16	30.9	57616.7
10%			Assig	ned F	ault				Dete	cted F	ault	
Artificial Fault	Data No.	Tcl	Tr	Vs	OA(%)	RMSE	Data No.	Tcl	Tr	Vs	OA(%)	RMSE
	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
Two	9	45	73	1.2	3	2628635.0	9	47.7	73.2	1.32	2.9	57229.0
Variable	10	65	73	1.2	30	542544.3	10	65.6	72.8	1.37	26.8	57195.7
Fault	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	16/3150.0	14	54.7	78.4	1.17	30.7	5/616./
	15	55	73	0.4	3	1463464.2	15	52.4	73.2	0.35	3.6	58032.3
	10											
	10	55	73	0.4	30	1212904.0	10	55.5	73.1	0.41	29.0	56005.7
	10	55	73	0.4	- 30	1212904.0	10	55.5	73.1	0.41	29.0	56003.7
10%		55	Assig	ined F	ault	1212904.0	10	55.5	Dete	cted F	ault	56005.7
10% Artificial Fault	Data No.	Tcl	Assig Tr	ined F Vs	-ault OA(%)	RMSE	Data No.	Tcl	Dete Tr	cted F Vs	ault OA(%)	RMSE
10% Artificial Fault	Data No. 17	Tcl	Assig Tr 68	ined F Vs 0.4	-ault OA(%) 10	RMSE 1254542.7	Data No. 17	Tcl 48.0	Dete Tr 67.6	cted F Vs 0.47	23.0 ault OA(%) 8.8	RMSE 58000.6
10% Artificial Fault	Data No. 17 18	Tcl 45 65	Assig Tr 68 78	0.4 Jned F Vs 0.4 0.4	-ault OA(%) 10 10	RMSE 1254542.7 1572491.5	Data No. 17 18	Tcl 48.0 69.5	Dete Tr 67.6 76.6	0.41 Cted F Vs 0.47 0.77	23.0 ault OA(%) 8.8 6.2	RMSE 58000.6 56069.0
10% Artificial Fault	Data No. 17 18 19	Tcl 45 65 45	Assig Tr 68 78 68	uned F Vs 0.4 0.4 1.2	-ault OA(%) 10 10 3	RMSE 1254542.7 1572491.5 1853217.7	Data No. 17 18 19	Tcl 48.0 69.5 43.0	Dete Tr 67.6 68.8	0.41 Vs 0.47 0.77 1.07	CA(%) 8.8 6.2 3.4	RMSE 58000.6 56069.0 57735.5
10% Artificial Fault Three	Data No. 17 18 19 20	Tcl 45 65 45	Assig Tr 68 78 68 78 68 78	0.4 Jned F Vs 0.4 0.4 1.2 1.2	-ault OA(%) 10 10 30	RMSE 1254542.7 1572491.5 1853217.7 59617.6	To Data No. 17 18 19 20	Tcl 48.0 69.5 43.0 65.0	Dete Tr 67.6 68.8 78.2	cted F Vs 0.47 0.77 1.07 1.20	^{23.0} ^{0A(%)} 8.8 6.2 3.4 30.0	RMSE 58000.6 56069.0 57735.5 58265.5
10% Artificial Fault Three Variable	Data No. 17 18 19 20 21	Tcl 45 65 65 55	Assig Tr 68 78 68 78 68 68 68	ned F Vs 0.4 0.4 1.2 1.2 0.4	-ault OA(%) 10 30 30 30	RMSE 1254542.7 1572491.5 1853217.7 59617.6 1645993.1	Data No. 17 18 19 20 21	Tcl 48.0 69.5 43.0 65.0 52.9	Dete Tr 67.6 68.8 78.2 67.9	cted F Vs 0.47 0.77 1.07 1.20 0.35	ault OA(%) 8.8 6.2 3.4 30.0 3.6	RMSE 58000.6 56069.0 57735.5 58265.5 58265.5
10% Artificial Fault Three Variable Fault	Data No. 17 18 19 20 21 22	Tcl 45 65 65 55 55	Assig Tr 68 78 68 78 68 78 68 78 68 78	0.4 Jned F Vs 0.4 0.4 1.2 1.2 0.4 0.4	-ault OA(%) 10 10 30 30 30 30	RMSE 1254542.7 1572491.5 1853217.7 59617.6 1645993.1 1031535.6	To Data No. 17 18 19 20 21 22	Tcl 48.0 69.5 43.0 65.0 52.9 54.7	Dete Tr 67.6 76.6 68.8 78.2 67.9 78.5	cted F Vs 0.47 0.77 1.07 1.20 0.35 0.39	ault OA(%) 8.8 6.2 3.4 30.0 3.6 30.9	RMSE 58000.6 56069.0 57735.5 58265.5 58072.5 58087.7
10% Artificial Fault Three Variable Fault	Data No. 17 18 19 20 21 22 23	Tcl 45 65 65 55 55 55 55	Assig Tr 68 78 68 78 68 78 68 78 68 78 73	0.4 Jned F Vs 0.4 0.4 1.2 1.2 0.4 0.4 0.4	-ault OA(%) 10 10 30 30 30 30	RMSE 1254542.7 1572491.5 1853217.7 59617.6 1645993.1 1031535.6 865657.4	Data No. 17 18 19 20 21 22 23	Tcl 48.0 69.5 43.0 65.0 52.9 54.7 45.0	Dete Tr 67.6 68.8 78.2 67.9 78.5 73.5	cted F Vs 0.47 0.77 1.07 1.20 0.35 0.39 0.40	ault OA(%) 8.8 6.2 3.4 30.0 3.6 30.9 30.5	RMSE 58000.6 56069.0 57735.5 58265.5 58072.5 58087.7 58016.3
10% Artificial Fault Three Variable Fault	Data No. 17 18 19 20 21 22 23 24	Tcl 45 65 65 55 55 45 65	Assig Tr 68 78 68 78 68 78 68 78 73 73 73	ned F Vs 0.4 0.4 1.2 1.2 0.4 0.4 0.4	-ault OA(%) 10 10 30 30 30 30 30	RMSE 1254542.7 1572491.5 1853217.7 59617.6 1645993.1 1031535.6 865657.4 1747628.2	To Data No. 17 18 19 20 21 22 23 24	Tcl 48.0 69.5 43.0 65.0 52.9 54.7 45.0 68.6	Dete Tr 67.6 68.8 78.2 67.9 78.5 73.5 73.3	cted F Vs 0.47 0.77 1.07 1.20 0.35 0.39 0.40 0.70	ault OA(%) 8.8 6.2 3.4 30.0 3.6 30.9 30.5 2.2	RMSE 58000.6 56069.0 57735.5 58265.5 58072.5 58072.5 58016.3 58445.1
10% Artificial Fault Three Variable Fault	Data No. 17 18 19 20 21 22 23 24 25 20	Tcl 45 65 55 55 45 65 65 65	Assig Tr 68 78 68 78 68 78 68 73 73 73 68	0.4 jned F Vs 0.4 0.4 0.4 0.4 0.4 0.4 0.4 0.4	-ault OA(%) 10 10 30 30 30 30 30 30	RMSE 1254542.7 1572491.5 1853217.7 59617.6 1645993.1 1031535.6 865657.4 1747628.2 1705132.4	To Data No. 17 18 19 20 21 22 23 24 25	Tcl 48.0 69.5 43.0 65.0 52.9 54.7 45.0 68.6 65.9	Dete Tr 67.6 68.8 78.2 67.9 78.5 73.5 73.3 69.0	cted F Vs 0.47 0.77 1.07 1.20 0.35 0.39 0.40 0.70 1.20	² 3.0 OA(%) 8.8 6.2 3.4 30.0 3.6 30.9 30.5 2.2 3.2 3.2	RMSE 58000.6 56069.0 57735.5 58265.5 58072.5 58087.7 58016.3 58445.1 58576.0
10% Artificial Fault Three Variable Fault	Data No. 17 18 19 20 21 22 23 24 25 26	Tcl 45 65 55 55 55 55 65 65 65 65 45	Assig Tr 68 78 68 78 68 78 68 73 73 73 68 78 73	0.4 Jned F Vs 0.4 0.4 1.2 0.4 0.4 0.4 0.4 0.4 1.2 1.2	-ault OA(%) 10 10 30	RMSE 1254542.7 1572491.5 1853217.7 59617.6 1645993.1 1031535.6 865657.4 1747628.2 1705132.4 3419432.6	To Data No. 17 18 19 20 21 22 23 24 25 26	Tcl 48.0 69.5 43.0 65.0 52.9 54.7 45.0 68.6 65.9 44.8	Dete Tr 67.6 68.8 78.2 67.9 78.5 73.5 73.3 69.0 78.3	cted F Vs 0.47 0.77 1.07 1.20 0.35 0.39 0.40 0.70 1.20 1.19	ault OA(%) 8.8 6.2 3.4 30.0 3.6 30.9 30.5 2.2 3.2 30.4	RMSE 58000.6 56069.0 57735.5 58065.5 58072.5 58072.5 58087.7 58016.3 58445.1 58576.0 57651.5
10% Artificial Fault Three Variable Fault	Data No. 17 18 19 20 21 22 23 24 25 26	Tcl 45 65 45 65 55 55 55 65 65 65 45	Assig Tr 68 78 68 78 68 78 68 73 73 73 68 78 73	0.4 Ined F Vs 0.4 0.4 1.2 0.4 0.4 0.4 0.4 0.4 1.2 1.2	-ault OA(%) 10 10 30	RMSE 1254542.7 1572491.5 1853217.7 59617.6 1645993.1 1031535.6 865657.4 1747628.2 1705132.4 3419432.6	Data No. 17 18 19 20 21 22 23 24 25 26	Tcl 48.0 69.5 43.0 65.0 52.9 54.7 45.0 68.6 65.9 44.8	Dete Tr 67.6 68.8 78.2 67.9 78.5 73.5 73.3 69.0 78.3	cted F Vs 0.47 0.77 1.07 1.20 0.35 0.39 0.40 0.70 1.20 1.19	ault OA(%) 8.8 6.2 3.4 30.0 3.6 30.9 30.5 2.2 3.2 30.4	RMSE 58000.6 56069.0 57735.5 58265.5 58072.5 58072.5 58016.3 58445.1 58576.0 57651.5
10% Artificial Fault Three Variable Fault 10%	Data No. 17 18 19 20 21 22 23 24 25 26	Tcl 45 65 45 55 55 55 45 65 65 45	Assig Tr 68 78 68 78 68 78 73 73 68 73 73 68 78 78 78	ned F Vs 0.4 0.4 1.2 1.2 0.4 0.4 0.4 0.4 0.4 1.2 1.2 1.2	-ault OA(%) 10 10 30 30 30 30 30 30 30 30 30	RMSE 1254542.7 1572491.5 1853217.7 59617.6 1645993.1 1031535.6 865657.4 1747628.2 1705132.4 3419432.6	Data No. 17 18 19 20 21 22 23 24 25 26	Tcl 48.0 69.5 43.0 65.0 52.9 54.7 45.0 68.6 65.9 44.8	Dete Tr 67.6 68.8 78.2 67.9 78.5 73.5 73.5 73.3 69.0 78.3 0 9.0 78.3	cted F Vs 0.47 0.77 1.20 0.35 0.39 0.40 0.70 1.20 1.19 cted F	ault OA(%) 8.8 6.2 3.4 30.0 30.5 2.2 30.5 2.2 30.4	RMSE 58000.6 56069.0 57735.5 58265.5 58072.5 58072.5 58016.3 58445.1 58576.0 57651.5
10% Artificial Fault Three Variable Fault 10% Artificial Fault	Data No. 17 18 19 20 21 22 23 24 25 26 Data No.	Tcl 45 65 45 55 55 55 65 65 65 65 45 7cl	Assig Tr 68 78 68 78 68 78 68 73 73 68 73 73 68 78 73 73 68 78 73 73 73 73 73 73 73 73 73 73 73	ned F Vs 0.4 0.4 1.2 1.2 0.4 0.4 0.4 0.4 0.4 1.2 1.2 1.2 Vs	-ault OA(%) 10 10 30 30 30 30 30 30 30 30 -ault OA(%)	RMSE 1254542.7 1572491.5 1853217.7 59617.6 1645993.1 1031535.6 865657.4 1747628.2 1705132.4 3419432.6 RMSE	To Data No. 17 18 19 20 21 22 23 24 25 26 Data No.	Tcl 48.0 69.5 43.0 65.0 52.9 54.7 45.0 68.6 65.9 44.8	Dete Tr 67.6 76.6 68.8 78.2 67.9 78.5 73.5 73.3 69.0 78.3 0 Dete Tr	cted F Vs 0.47 0.77 1.20 0.35 0.39 0.40 0.70 1.20 1.19 cted F Vs	ault OA(%) 8.8 6.2 3.4 30.0 3.6 30.9 30.5 2.2 30.5 2.2 30.4	RMSE 58000.6 56069.0 57735.5 58265.5 58072.5 58072.5 58016.3 58445.1 58576.0 57651.5 RMSE
10% Artificial Fault Three Variable Fault 10% Artificial Fault	Data No. 17 18 19 20 21 22 23 24 25 26 Data No. 27	Tcl 45 65 45 65 55 55 55 65 65 65 65 45 7cl	Assig Tr 68 78 68 78 68 78 68 73 73 68 73 68 78 73 73 68 78 73 73 68 78 78 73 68 78 78 78 78 78 78 78 78 78 78 78 78 78	ned F Vs 0.4 0.4 1.2 1.2 0.4 0.4 0.4 0.4 1.2 1.2 1.2 1.2 yned F Vs 0.4	ault OA(%) 10 10 30	RMSE 1254542.7 1572491.5 1853217.7 59617.6 1645993.1 1031535.6 865657.4 1747628.2 1705132.4 3419432.6 RMSE 1882528.4	To Data No. 17 18 19 20 21 22 23 24 25 26 Data No. 27	Tcl 48.0 69.5 43.0 65.0 52.9 54.7 45.0 68.6 65.9 44.8 Tcl 66.6	Dete Tr 67.6 68.8 78.2 67.9 78.5 73.5 73.3 69.0 78.3 69.0 78.3 73.3 69.0 78.3	cted F Vs 0.47 0.77 1.07 1.20 0.35 0.39 0.40 0.70 1.20 1.19 cted F Vs 0.71	ault OA(%) 8.8 6.2 3.4 30.0 3.6 30.9 30.5 2.2 30.4 30.4 30.5 2.2 30.4	RMSE 58000.6 56069.0 57735.5 58072.5 58072.5 58072.5 58016.3 58445.1 58576.0 57651.5 57651.5 87651.5
10% Artificial Fault Three Variable Fault 10% Artificial Fault Four	Data No. 17 18 19 20 21 22 23 24 25 26 Data No. 27 28	Tcl 45 65 45 65 55 55 55 65 65 65 45 7cl 7cl	Assig Tr 68 78 68 78 68 78 68 73 73 68 73 73 68 78 73 73 73 73 68 78 78	0.4 med F Vs 0.4 0.4 1.2 0.4 0.4 0.4 0.4 1.2 1.2 0.4 0.4 0.4 0.4 0.4 0.4 0.4 0.4	Fault OA(%) 10 10 30 30 30 30 30 30 30 30 30 5 ault OA(%) 30	RMSE 1254542.7 1572491.5 1853217.7 59617.6 1645993.1 1031535.6 865657.4 1747628.2 1705132.4 3419432.6 RMSE 1882528.4 747652.6	To Data No. 17 18 19 20 21 22 23 24 25 26 Data No. 27 28	Tcl 48.0 69.5 43.0 65.0 52.9 54.7 45.0 68.6 65.9 44.8 Tcl 66.6 44.6	Dete Tr 67.6 68.8 78.2 67.9 78.5 73.5 73.5 73.3 69.0 78.3 69.0 78.3 Dete Tr 68.4 78.6	cted F Vs 0.47 0.77 1.07 1.20 0.35 0.39 0.40 0.70 1.20 1.19 cted F Vs 0.71 0.39	ault OA(%) 8.8 6.2 3.4 30.0 30.5 2.2 30.5 2.2 30.4 30.4 CA(%) 2.0 30.8	RMSE 58000.6 56069.0 57735.5 58265.5 58072.5 58072.5 58016.3 58445.1 58576.0 57651.5 57651.5 RMSE 59002.2 57723.0
10% Artificial Fault Three Variable Fault 10% Artificial Fault Four Variable	Data No. 17 18 19 20 21 22 23 24 25 26 26 Data No. 27 28 29	Tcl 45 65 45 55 55 55 45 65 65 45 65 7cl 55 65 65 65 65 65	Assig Tr 68 78 68 78 68 78 73 73 68 78 73 68 78 78 78 78 78 78	ned F Vs 0.4 0.4 1.2 1.2 0.4 0.4 0.4 0.4 1.2 1.2 1.2 1.2 0.4 0.4 0.4 0.4 0.4 0.4 0.4	-ault OA(%) 10 10 30 30 30 30 30 30 30 30 30 30 30 30 30	RMSE 1254542.7 1572491.5 1853217.7 59617.6 1645993.1 1031535.6 865657.4 1747628.2 1705132.4 3419432.6 RMSE 1882528.4 747652.6 1609367.3	To Data No. 17 18 19 20 21 22 23 24 25 26 Data No. 27 28 29	Tcl 48.0 69.5 43.0 65.0 52.9 54.7 45.0 68.6 65.9 44.8 Tcl 666.6 44.6 69.5	Dete Tr 67.6 68.8 78.2 67.9 78.5 73.5 73.5 73.3 69.0 78.3 69.0 78.3 0 78.3 5 73.3 69.0 78.3 73.3 69.0 78.3 69.0 78.3	cted F Vs 0.47 0.77 1.07 1.20 0.35 0.39 0.40 0.70 1.20 1.19 cted F Vs 0.71 0.39 0.69	ault OA(%) 8.8 6.2 3.4 30.0 30.5 2.2 30.5 2.2 30.4 30.5 2.2 30.4 CA(%) 2.0 30.8 2.3	RMSE 58000.6 56069.0 57735.5 58265.5 58072.5 58072.5 58016.3 58445.1 58576.0 57651.5 57651.5 8 RMSE 59002.2 57723.0 57465.8

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

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



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