Investigation of Reliability of Hydraulic Robots for Hazardous Environments Using Analytic Redundancy

Martin L. Leuschen • Rice University • Houston

Ian D. Walker • Clemson University • Clemson

Joseph R. Cavallaro • Rice University • Houston

Key Words: Fault Detection, Robotics, Simulation.

SUMMARY & CONCLUSIONS

Robotics for hazardous environments is one of the most important and fast growing areas in the robotics industry [4, 5, 6, 12]. This area focuses on providing a high level functionality in arenas where humans cannot safely or cheaply work. However, the usefulness of the robot in hazardous situations is highly dependent on its reliability. Hazardous environments can damage robotic components, are often sensitive to disturbances that can be caused by malfunctioning robots, and humans usually cannot enter these areas to repair or remove a failed robot. For these reasons, our team has investigated reliability issues for robots extensively [7, 8, 14, 9].

The Rosie mobile worksystem [1, 3] is an important and interesting robot that is on the cutting edge of hazardous environment robotics. (DOE is currently using it in the decommissioning of Argonne National Laboratory's CP-5 reactor facility [1].) Rosie, under development by RedZone Robotics Inc. and Carnegie Mellon University's Field Robotics Center, is a heavy-duty hydraulic robot designed for nuclear reactor decontamination and dismantlement. The robot consists of a wheeled platform containing a central hydraulic power supply powered by an electric tether, four independently steerable wheels, and a heavy-duty crane/manipulator. The hydraulic wheel actuator subsystem has been determined to be a vital component of the mobile platform through reliability analysis. A failure of a wheel mechanism may prevent the removal of Rosie from the reactor work site, which may very well be deadly to potential repairmen.

The combination of the hazardous nuclear environment and debris from the decontamination and dismantlement tasks will put considerable stress on the robot system and requires a careful monitoring and diagnostics strategy to reduce the possibility of major failures. Our research into analyzing this robot's reliability through the technique of analytical redundancy (AR) will help provide the Department of Energy (DOE) with a more complete and effective set of tests for monitoring and diagnostics of the Rosie system.

In this paper, we discuss the derivation through AR of a suite of model based tests for the default sensor package for one of Rosie's wheel actuators. AR allows us to exploit the sensor information of the sensors values and the system model to derive tests of the consistency of the sensor data. Some of these tests are comparison of the actual system response to control inputs to predicted response indicated by the model, the other tests uncovered by the AR analysis reflect higher order state interdependencies. These tests and their use in monitoring and diagnostics for Rosie are detailed and examined in depth. This work is also an interesting example of the application of model based techniques for an important class of practical systems.

1. INTRODUCTION

Our research group is working with Foster-Miller Technologies Incorporated, an organization with considerable experience in evaluating the reliability of hydraulic systems, as part of a DOE contract to examine monitoring and diagnostic issues for Rosie. The project goal is to develop and test effective sensor configurations and data analysis procedures to minimize the negative impact of failures of the Rosie worksystem. While constraints prevent us from implementing major physical modifications

to Rosie, we will demonstrate how significant reliability improvements can be gained through effective use of monitoring and diagnostic techniques.

The paper will focus on *analytical redundancy* [2], or AR. AR is a model-based technique that derives the maximum number of independent tests of the consistency of sensor data with the nominal model and past control inputs, which yields tests to determine whether the system is performing nominally, or is under fault conditions. Our group has used this technique successfully on electrical robotic systems in the past [13], and is now applying it to the hydraulic Rosie system. The hydraulic nature of the system changes failure modes and sensor configurations significantly and thus requires new analysis.

Notation

j , and i are generic subscripts, k is the discrete time variable

N is the # of states in a system, $\underline{x} \in R^N$ is the state vector

q is the # of control inputs in a system, u_j is the j th control input

m is the # of sensors in a system, and y_j is the output from the j -th sensor

A is a $N \times N$ state transition matrix

b_j is a $N \times 1$ column vector, c_j is a $1 \times N$ row vector. (Standard state control model vectors).

W ($N \times 1$) and V (1×1) represent noise, nonlinearity and model error.

C_j is the j th observability matrix (Note that this is different than the standard notation, where C is usually a controllability matrix.)

Q is the net fluid flow through the system

x_v is the servovalve spool position (control variable)

K_f is the experimentally determined flow constant

ρ is the hydraulic fluid density

p_s is the supply pressure

p_l is the load pressure drop across the motor

d_m is the volumetric displacement of the motor

c_{im} and c_{em} are experimentally determined internal and external leak coefficients

v_t is the volume of fluid within the motor

β_e is the bulk modulus of the hydraulic fluid.

k_q and k_c are experimentally determined linear flow coefficients

T_g is the torque generated by the hydraulic system

J_t is the inertia of the motor plus load

B_m is the viscous damping coefficient

T_l is the load torque.

F_j is the j th derived AR test

n_0 is the maximum rank of all the C_j matrices

$M = k_c + c_{em} + c_{im}$

Δt is the time step

$\theta(k)$ is the angular shaft position

$p(k)$ is the pressure drop across the motor (p_l) at time k

$\underline{x}(k) = [\theta(k) \dot{\theta}(k) p(k)]^T$

2. ANALYTICAL REDUNDANCY

The analytical redundancy (AR) method allows us to explicitly derive the maximum possible number of linearly independent consistency tests for a system [2]. Using a linear model of the system of interest, AR exploits the null space of the observability matrix to allow the creation of a set of test equations. These tests use sensor data histories and known past control inputs to detect any deviation whatsoever from the static or dynamic behaviors of the model. The deviations can then be analyzed for signs that indicate specific faults within the system.

A major advantage of AR is that the technique has already removed the model-following aspects of the sensor data, leaving only the deviations from the model characteristics inherent in the individual AR tests. In addition to allowing better model tuning, this reduces the amount of "noise" the error detection software has to deal with, making isolating faults that much easier. Although the faults may be visible in the sensor data streams, AR will isolate them from expected behavior, and categorize them according to the AR tests.

AR works using the standard discrete linear control model with N states, q control inputs, and m sensors:

$$\underline{x}(k+1) = [A]\underline{x}(k) + \sum_{j=1}^q b_j u_j(k) + W, \quad (1)$$

$$y_j(k) = c_j \underline{x}(k) + V, \quad j = 1, \dots, m \quad (2)$$

Since the values of the matrices W and V cannot be predicted, they are not considered in the following derivations, and will be dealt with later as noise in the derived tests.

The canonical observability matrices for the above system are: $C_j(k) = [c_j^T, (c_j A)^T, \dots, (c_j A^{k-1})^T]$, $j = 1, \dots, m$; $k = 1, \dots$. In addition to their standard properties (see any good book on control theory), the ranks (r_j) of these matrices indicate how many time steps of observation are necessary to gain all the information available on the system. For AR purposes, we shall keep $r_j + 1$ rows of each matrix to define a (non-unique) Ω matrix representing the unobservable part of the workspace:

$$[\Omega] \begin{bmatrix} C_1 \\ C_2 \\ \vdots \end{bmatrix} \underline{x}(k) = 0. \quad (3)$$

Each row of Ω , when directly multiplied by the state-history vector $\underline{x}_h(k) = [x_1(k) \ x_1(k+1) \ \dots \ x_2(k) \ x_2(k+1) \ \dots]^T$, will have a zero result in the ideal case. The real case, with W and V included, will have small errors.

However, this result uses the state histories of the system, and we only indirectly know these values. We must define our tests in terms of the known values of y , b , and $u(k)$. The resulting parity vector $P(k)$ is defined as follows, with the term in curly braces replacing the $[C]\underline{x}$ from equation 3 :

$$P(k) = \Omega \left\{ \begin{bmatrix} Y_1(k, n_1) \\ \vdots \\ Y_m(k, n_m) \end{bmatrix} - \begin{bmatrix} B_1(n_1) \\ \vdots \\ B_m(n_m) \end{bmatrix} U_{k, n_0} \right\}, \quad (4)$$

where

$$Y_i(k, n_i) = \begin{bmatrix} y_i(k) \\ y_i(k+1) \\ \vdots \\ y_i(k+n_i) \end{bmatrix}$$

and

$$B_i(n_i) = \begin{bmatrix} 0 & 0 & \dots & 0 \\ c_i b & 0 & \dots & 0 \\ \vdots & c_i b & \dots & 0 \\ \vdots & \vdots & \dots & \vdots \\ c_i A^{n_i-1} b & c_i A^{n_i-2} & \dots & c_i b \end{bmatrix},$$

$i = 1, \dots, m$.

Note that this last operation is mathematically intensive since it is running the model backwards to get the states from the outputs. The Y_i matrices supply the histories of the sensor values while the $[B]U$ term uses the dynamic model and control input history to convert these sensor histories back into the state history they were derived from.

The resulting $P(k)$ is an array of tests that will equal zero in the ideal case. In the case of real sensor data, the deviations from zero should be indicative of modeling inaccuracies, noise, and faults, with any model-following behavior completely masked. In the following section, the AR procedure documented here shall be performed on an actuator from the Rosie robot.

3. MODELING ROSIE

As discussed above, the wheel actuators are a critical component of the Rosie robot. Each actuator consists of a high-performance hydraulic rotary motor connected to a 3000 PSI hydraulic power source through a hydraulic spool valve. Sensors showing the current angular position of the motor shaft and the pressure drop across it monitor the system. The system and locations of the investigated faults can be seen below in figure 1.

The model for hydraulic fluid flow through the spool valve is system is [11]:

$$Q = x_v K_f \sqrt{\frac{2}{\rho} (p_s - p_l)} = d_m \dot{\theta}_m + (c_{im} + c_{em}) p_l + \frac{v_t \dot{p}_l}{4\beta_e} \quad (5)$$

Unfortunately, the model above is nonlinear, and thus not amenable to linear AR methods. We will instead derive our AR tests from the linear version [11]:

Figure 1: Wheel actuator system.

$$Q = k_q x_v - k_c p_l = d_m \dot{\theta}_m + (c_{im} + c_{em}) p_l + \frac{v_t \dot{p}_l}{4\beta_e} \quad (6)$$

The inaccurate linearity of this approximation will show up as increased noise in our parity tests, but this is currently unavoidable. A comparison of the two models for representative parameter values is shown in figure 2.

Figure 2: Percentage error for linear approximation

It can be seen that the greatest errors in this model occur during high pressures or valve positions far from the mid range value of 0.3 in. While this is satisfactory for control purposes (best control in the middle of the operating region) it is less desirable for fault detection, as faults are more likely to occur under extreme conditions. However, AR is already designed to deal with nonlinearities as noise, so this is not necessarily a critical issue for our application.

The extension of the linear AR techniques to explicitly handle the nonlinearities in the model, and application of nonlinear techniques for fault detection in the nonlinear regions of the model are open areas of research which we are currently actively pursuing. At the present time however, linear techniques such as AR, as analyzed for Rosie in this paper, represent the state of the art in fault detection. Thus the results here (the first time AR has been applied to hydraulic robots to the best of our knowledge) will provide a benchmark for later efforts.

The model for the generated torque is as follows [15]:

$$T_g = p_l d_m = J_t \ddot{\theta}_m + B_m \dot{\theta}_m + T_l, \quad (7)$$

Using these two linear model equations 7, 6, we can construct a standard linear discrete-time control model of the system, as follows:

$$A = \begin{bmatrix} 1 & \Delta t & 0 \\ 0 & \frac{J_t - B_m \Delta t}{J_t} & \frac{d_m \Delta t}{J_t} \\ 0 & \frac{-4\beta_e d_m \Delta t}{v_t} & \frac{v_t - 4\beta_e M \Delta t}{v_t} \end{bmatrix},$$

$$B = \begin{bmatrix} 0 \\ 0 \\ \frac{4\beta_e k_q \Delta t}{v_t} \end{bmatrix}, \text{ and } C = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}.$$

By following the procedure in the previous section, the following tests can be derived:

$$P_1 = \frac{J_t - B_m \Delta t}{J_t} \theta(k) + \frac{(B_m \Delta t - 2J_t)}{J_t} \theta(k+1) + \theta(k+2) - \frac{d_m \Delta t^2}{J_t} p(k) \quad (8)$$

$$P_2 = \left(\frac{-3B_m \Delta t}{J_t} + \frac{B_m^2 \Delta t^2}{J_t^2} + \frac{-4\beta_e d_m^2 \Delta t^2}{J_t v_t} \right) (\theta(k) - \theta(k+1))$$

$$+ (2\theta(k) - 3\theta(k+1) + \theta(k+3)) - \frac{(4d_m \beta_e k_q \Delta t^3)}{J_t v_t} x_v(k)$$

$$+ \left(\frac{-3d_m \Delta t^2}{J_t} + \frac{d_m B_m \Delta t^2}{J_t^2} + \frac{4\beta_e d_m M \Delta t^3}{J_t v_t} \right) p(k) \quad (9)$$

$$P_3 = \frac{4\beta_e d_m}{v_t} (\theta(k+1) - \theta(k)) - \frac{k_q \Delta t}{d_m} x_v(k) + \frac{4\beta_e M \Delta t}{v_t} p(k) + p(k+1) - p(k) \quad (10)$$

$$P_4 = \left(\frac{4B_m \beta_e d_m \Delta t}{J_t v_t} + \frac{4\beta_e^2 d_m M \Delta t}{v_t^2} + \frac{-2\beta_e d_m}{v_t} \right) (\theta(k) - \theta(k+1))$$

$$+ \left(-1 + \frac{8\beta_e M \Delta t}{v_t} + \frac{4\beta_e d_m^2 \Delta t^2}{v_t J_t} + \frac{-16\beta_e^2 M^2 \Delta t^2}{v_t^2} \right) p(k)$$

$$+ p(k+2) + \frac{4\beta_e k_q \Delta t}{v_t} \left(\frac{(4\beta_e M \Delta t - v_t)}{v_t} x_v(k) - x_v(k+1) \right) \quad (11)$$

Note that tests P_1 and P_3 are much simpler than tests P_2 and P_4 . This is because the odd numbered tests can be shown to be digital analogues of the actual model equations. P_1 is equivalent to equation 7, while P_3 is equivalent to equation 6. This is reassuring, as it confirms that our analysis was valid. The even numbered tests are more complex, and test for higher order behaviors of the system. For example, we have shown that P_2 is the derivative of P_1 , and P_4 is the derivative of P_3 .

4. IMPLEMENTATION

Our preliminary analysis was performed on a complex Simulink [10] model of the system. The nonlinear model of equation 5 was used, with additional subsystems added to represent pressure saturation, dither, friction, and noise. Although we will shortly be analyzing raw data from the Foster-Miller physical hydraulic testbed [9], this platform is currently under construction, and will be examined in a later phase of the project.

Figures 3 and 4 show the fault free response of the system to a step input and a ramp input respectively. (Note that the plot values have each been multiplied by a scalar for ease of reading. Multiply velocity by 50 rads/s and pressure by 3000 PSI for the true values. For the P_i tests relative scale between figures is maintained for the

Figure 3: Fault free signals (Step).

same i , as relative form and magnitude are most important.) The noise in the pressure signal does not have a large effect on the velocity signal due to the large time constant of hydraulic systems. Also note the large spikes in the AR tests at the time of the step in figure 3. These are an artifact of the discrete natures of the tests - large changes within a time step will reduce the effectiveness of discrete models. The decreased noise in the pressure signal at higher pressures seen in figure 4 is a result of the square-root nature of the servovalve mechanism shown by equation 5.

The small constant errors in the P_1 and P_2 tests are the result of the frictional effects in the model. We hope to use them to monitor the static and dynamic friction in the system. The large error in P_3 is due to the differences between the linear and nonlinear models. Although the error is large, some information can still be extracted from this signal. The dynamic pressure behavior of P_4 shows much smaller steady-state error, since the pressure is not changing much in this period.

Figure 5 shows the test signals for the step input when the model parameters have been increased by 10% for the model but not the test, showing some possible effects of parameter estimation error. Note that many of the steady state signals have moved, implying that good initial parameter estimation will be needed to consider the friction effects discussed above.

Figure 4: Fault free signals (Ramp).

Figure 6: Friction fault (Step).

Figure 5: Parameters underestimated.

Figure 7: Friction fault (Ramp).

A friction fault resulting in increased static friction (jamming that doesn't completely stop rotation) is shown in figures 6 and 7. The static friction of the system has been increased fifty fold at $t = 9$ seconds. Since this is a static problem with the motor subsystem, one would expect it to have the greatest effect on P_1 , which is the actual case.

Figure 8: Flow fault (Step).

Figure 9: Flow fault (Ramp).

A serious leak in the system somewhere before the servovalve (see fig 1) is the problem in figures 8 and 9 reducing the flow through the valve substantially. All of the tests are strongly affected by this problem.

All in all, the tests performed reasonably well. Faults

caused definite changes in the behavior of the error tests. These changes were distinctive for the two different faults, implying that fault identification through AR is feasible. Further research into this area is certainly warranted, as greater understanding of the results of these tests will lead to a greater understanding of the system itself.

5. FUTURE WORK

Our primary concern is to learn how to implement these tests on Foster-Miller's hydraulic testbed. (Currently under construction.) This will bring up the complex issues of fault detection in conjunction with parameter estimation, nonlinear system response, and variable and unpredictable loading [9]. Although our initial work with linear models has been interesting and productive, these areas promise to present further challenging research problems. The first to be tackled will be the nonlinear aspects, as this can be investigated to a large extent via computer models.

Additionally, we need to develop a general fault detection system for the testbed through practical use of our AR tests. It must be able to process the AR test signals and use a database based on experimental fault behavior to automatically detect and discriminate between various faults. Currently, a fuzzy expert system is being considered for this work.

6. ACKNOWLEDGMENTS

This work was supported in part by the National Science Foundation under grants IRI-9526363 and CMS 9796328, by DOE Sandia National Laboratory Contract #AL3017, and DOE contract DE-FG07-97ER 14830.

REFERENCES

- [1] L. C. Bares, L. S. Conley, and B.R. Thompson. Rosie: A Mobile Worksystem for D & D: Overview of System Capabilities and CP-5 Reactor Application. In *Proceedings of the ANS 7th Topical Meeting on Robotics and Remote Systems*, pages 471-477, Augusta, GA, April-May 1997.
- [2] E. Y. Chow and A. S. Willsky. Analytical Redundancy and the Design of Robust Failure Detection Systems. *IEEE Transactions on Automatic Control*, AC-29(7):603-614, July 1984.
- [3] L. Conley, Dr. W.R. Hamel, and B.R. Thompson. Rosie: A Mobile Worksystem for Decontamination and Dismantlement Operations. In *Proceedings of the ANS 6th Topical Meeting on Robotics and Remote Systems*, pages 231-238, Monterey, CA, February 1995.
- [4] Department of Energy, Washington, D.C. *Environmental Restoration and Waste Management 5-Year Plan, Fiscal Years 1994-1998*, January 1993. DOE/S-00097P, Vol. 1-2.
- [5] Department of Energy, Federal Energy Technology Center, Morgantown, WV. *Environmental Waste Management Project Fact Sheet*, October 1997. <http://www.fetc.doe.gov/publications/factsheets/ewm/index.html>.

- [6] B. S. Dhillon. *Robot Reliability and Safety*. Springer-Verlag, New York, NY, 1991.
- [7] B. M. Harpel, J. B. Dugan, I. D. Walker, and J. R. Cavallaro. Analysis of Robots for Hazardous Environments. In *Proc. IEEE Annual Reliability and Maintainability Symposium*, pages 111-116, Philadelphia, PA, January 1997.
- [8] M. L. Leuschen, I. D. Walker, and J. R. Cavallaro. Robot Reliability Through Fuzzy Markov Models. In *Proc. IEEE Annual Reliability and Maintainability Symposium*, pages 209-214, Anaheim, CA, January 1998.
- [9] M. L. Leuschen, I. D. Walker, and J. R. Cavallaro. Monitoring and Diagnostics for a Hydraulic Robot in Hazardous Environments. In *Proceedings of the ANS 8th Topical Meeting on Robotics & Remote Systems*, Pittsburgh, PA, April 1999. (to appear).
- [10] MathWorks. Simulink.
<http://www.mathworks.com/products/simulink/>.
- [11] W. Stadler. *Analytical Robotics and Mechatronics*. McGraw-Hill, Inc., New York, NY, 1995.
- [12] M. L. Visinsky, J. R. Cavallaro, and I. D. Walker. Robotic Fault Detection and Fault Tolerance: A Survey. *Reliability Engineering and System Safety*, 46(2):139-158, 1994.
- [13] M.L. Visinsky, J.R. Cavallaro, and I.D. Walker. A Dynamic Fault Tolerance Framework for Remote Robots. *IEEE Transactions on Robotics and Automation*, 11(4):477-490, 1995.
- [14] I. D. Walker and J. R. Cavallaro. The Use of Fault Trees for the Design of Robots for Hazardous Environments. In *Proc. IEEE Annual Reliability and Maintainability Symposium*, pages 229-235, Las Vegas, NV, January 1996.
- [15] F. M. White. *Fluid Mechanics*. McGraw-Hill, Inc., USA, 1994.

Author Information

Presenting Author

Martin L. Leuschen, *M.S.*
Department of Electrical and Computer Engineering
Rice University
6100 S. Main, MS 366
Houston, Texas 77005 USA
(Work)

Company Name: Rice University

Work Phone: (713) 527-8101x2256
Work Fax: (713) 524-5237
Home Phone: (713) 526-0441
Email: martinl@rice.edu

Brief Professional Biography

Martin L. Leuschen received the B.S. in Applied Physics degree from Angelo State University, San Angelo, TX, in 1995, and the M.S. degree in Electrical Engineering from Rice University, Houston, TX, in 1997. He is currently a graduate student in the Department of Electrical and Computer Engineering at Rice. His research interests include fuzzy logic and interval arithmetic, fault tolerance, and robotics.

Corresponding Author

Joseph R. Cavallaro, *Ph.D.*
Department of Electrical and Computer Engineering
Rice University
6100 S. Main, MS 366
Houston, Texas 77005 USA
(Work)

Company Name: Rice University

Work Phone: (713) 527-4719
Work Fax: (713) 524-5237
Home Phone: (281) 412-0133
Email: cavallar@rice.edu

Brief Professional Biography

Joseph R. Cavallaro received the B.S. degree from the University of Pennsylvania, Philadelphia, PA, in 1981, the M.S. degree from Princeton University, Princeton, NJ, in 1982, and the Ph.D. degree from Cornell University, Ithaca, NY, in 1988, all in electrical engineering. From 1981 to 1983, he was with AT&T Bell Laboratories, Holmdel, NJ. In 1988 he joined the faculty of Rice University, Houston, TX, where he is an Associate Professor of Electrical and Computer Engineering. His research interests include computer arithmetic, fault tolerance, VLSI design and microlithography, and VLSI architectures and algorithms for parallel processing and robotics.

Author

Ian D. Walker, *Ph.D.*
Department of Electrical and Computer Engineering
Clemson University
Clemson, SC 29634 USA
(Work)

Company Name: Clemson University

Work Phone: (864) 656-7209
Work Fax: (864) 656-7220
Email: ianw@ces.clemson.edu

Brief Professional Biography

Ian D. Walker received the B.Sc. degree in Mathematics from the University of Hull, England, in 1983. He received the M.S. degree in 1985, and the Ph.D. in 1989, both in Electrical Engineering, from the University of Texas at Austin. From 1989 until 1997 he was part of the faculty of Rice University, Houston, TX, where he became an Associate Professor. In 1997, he became an Associate Professor in Electrical and Computer Engineering at Clemson University, Clemson, SC. His research interests are in the areas of robotics and control, particularly fault tolerant robot systems, robotic hands and grasping, and kinematically redundant robots.