JOURNAL OF PROPULSION AND POWER
Vol. 18, No. 2, March–April 2002

Leak Fault Detection of Liquid Rocket Engine Based on Strong Tracking Filter

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The propellant leak is one of the most common and especially dangerous faults in liquid rocket engine (LRE). By analyzing the performance of the engine, we know that the leak of hydraulic lines can be expressed as the variation of the fluid resistance coefficients. If leaks occur in the hydraulic line, the corresponding fluid resistance coefficients will be changed. An approach is presented to detect and diagnose the leak of hydraulic line based on a strong tracking filter. The method uses a strong tracking filter to estimate the fluid resistance coefficients and to compare the estimated fluid resistance coefficients with their normal values. Then the modified bias method is used to detect the leak fault. We simulate the leaks occurring in the main system or in the subsidiary system of LRE. The results show that the approach is feasible.

Nomenclature

A_b = area of gas generator, m^2
A_f, B_f, C_f = coefficients for second-order polynomial fit for fuel pump pressure head curve
A_o, B_o, C_o = coefficients for second-order polynomial fit for oxidizer pump pressure head curve
A_t = area of combustion chamber, m^2
J = moment of inertia of turbopump system
k = time point of discrete equations
m_f = engine fuel mass flow rate, kg/s
m_{fb} = fuel mass flow rate at gas generator, kg/s
m_{fc} = fuel mass flow rate at combustion chamber, kg/s
m_i = liquid flow rate, kg/s
m_o = engine oxidizer mass flow rate, kg/s
m_{ob} = oxidizer mass flow rate at gas generator, kg/s
m_{oc} = oxidizer mass flow rate at combustion chamber, kg/s
n = turbopump shaft speed, rad/min
p_b = gas generator pressure, MPa
p_c = combustion chamber pressure, MPa
p_f^l = pressure at position B, MPa
p_{if} = fuel pressure before injecting, MPa
p_{oi} = oxidizer pressure before injecting, MPa
p_o^l = pressure at position A, MPa
p_1 = pressure of input, MPa
p_2 = pressure of output, MPa
R = gas constant
r_b = propellant mass mixture ratio at gas generator
r_c = propellant mass mixture ratio at combustion chamber
T_b = temperature of gas generator, K
T_c = temperature of combustion chamber, K
T_t = temperature of turbopump, K
$\boldsymbol{u}(\cdot)$ = input vector
V_b = volume of gas generator, m^3
V_c = volume of combustion chamber, m^3
$\boldsymbol{x}(\cdot)$ = state vector
$\boldsymbol{y}(\cdot)$ = measurement vector
α = exponent of hot-gas expansion
β = turbine hot-gas inlet pressure to outlet pressure
Γ = property groups, $\sqrt{\{\alpha[2/(\alpha+1)]^{(\alpha+1)/(\alpha-1)}\}}$
η_o, η_f, η_t = efficiency
λ = coefficients
ξ_i = fluid resistance coefficients
ρ, ρ_o = propellant density, kg/m^3

Subscripts

b = gas generator
c = combustion chamber
f = fuel
o = oxidizer

Received 22 May 2000; revision received 8 June 2001; accepted for publication 29 September 2001.

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Introduction

IN the aerospace industry, propellant leaks pose significant operation problems. In 1990, the STS fleet experienced excessive hydrogen leaks in the main propulsion system before launches of STS-35 and STS-38 and during the flight of STS-41. The prelaunch leaks experienced by STS-35 and STS-38 resulted in a temporary grounding of the fleet until the leak source could be identified.[1]

The problem of detecting or diagnosing faults and digressions in complex rocket engines has attracted considerable attention recently. Current research in the development of detection and diagnosis systems for the propulsion systems focuses on such approaches as expert systems,[2] neural networks,[3] and signal processing.[4]

Currently, many techniques are used for detecting leaks in practice, for example, the hydrogen leak system techniques for detection of leaks in a rocket engine component.[5] All of the mentioned techniques for detection and diagnosis of leaks are based on sensors and make the sensor systems of rocket engine too complicated to keep the systems integrated.

An approach based on a strong tracking filter for leak fault detection and diagnosis, which belongs in the field of model-based fault detection and diagnosis is discussed. The strong tracking filter is a modification of the extended Kalman filter. It is based on the following performance indices. The mean square of estimated residues is minimum, and the residues satisfy the orthogonality condition. Thus, if the model parameters mismatch, the gain matrix of the filter can be adjusted to tracking the actual states at real time. This approach is suitable for joint state and parameter estimation.[6]

Analyzing the performance of a liquid rocket engine (LRE), we can deduce that the leaks of the hydraulic line can be attributed to the variations of the fluid resistance coefficients. Therefore, we use a strong tracking filter to estimate the variation of fluid resistance coefficients and to compare the estimated fluid resistance coefficients with their normal values. The residues could be obtained.

According to the residues, the leaks can be detected by the modified bias method.[6]

LRE Mathematical Models

A propellant flow schematic of the LRE with a turbopump system is shown in Fig. 1. In Fig. 1, control gas lines and pressured system lines are not shown. The portion from the position of pipeline offset (A and B) to the combustion chamber is the main system, and the portion from the position of pipeline offset (A and B) to the gas generator is the subsidiary system.

The full-order dynamic model of the engine has been set up, but it is not suitable for filter design because it is too complex. When the main operating principles during the steady main stage and transient performance at the rated operating point nearby are considered and at the same time the models are compromised in accuracy and complexity, the nonlinear dynamic models that are used for filter design are built and given as follows.

Combustion chamber dynamic equations:

$$\frac{\mathrm{d}p_c}{\mathrm{d}t} = \frac{1}{V_c}\left[RT_c + \frac{\partial RT_c}{\partial r_c}(1+r_c)\right]\dot{m}_{oc} + \frac{1}{V_c}\left[RT_c - \frac{\partial RT_c}{\partial r_c}(1+r_c)r_c\right]\dot{m}_{fc} - \frac{1}{V_c}\sqrt{RT_c}\Gamma A_t p_c \tag{1}$$

$$\frac{\mathrm{d}r_c}{\mathrm{d}t} = \frac{RT_c}{V_c p_c}(1+r_c)(\dot{m}_{oc} - r_c\dot{m}_{fc}) \tag{2}$$

Gas generator dynamic equations:

$$\frac{\mathrm{d}p_b}{\mathrm{d}t} = \frac{1}{V_b}\left[RT_b + \frac{\partial RT_b}{\partial r_b}(1+r_b)\right]\dot{m}_{ob} + \frac{1}{V_b}\left[RT_b - \frac{\partial RT_b}{\partial r_b}(1+r_b)r_b\right]\dot{m}_{fb} - \frac{1}{V_b}\sqrt{RT_b}\Gamma A_b p_b \tag{3}$$

$$\frac{\mathrm{d}r_b}{\mathrm{d}t} = \frac{RT_b}{V_b p_b}(1+r_b)(\dot{m}_{ob} - r_b\dot{m}_{fb}) \tag{4}$$

Equations of turbopump (ignoring the variety of propellant density and temperature):

$$\frac{\mathrm{d}n}{\mathrm{d}t} = \frac{900}{\pi^2 Jn}\left[\Gamma_b A_b p_b \eta_t\left(\frac{a}{a-1}\right)\left(1-\beta^{(a-1)/a}\right)\sqrt{RT_t} - \frac{1}{\eta_o\rho_o}\left(A_o n^2 + B_o n\dot{m}_o + C_o\dot{m}_o^2\right) - \frac{1}{\eta_f\rho_f} \times \left(A_f n^2 + B_f n\dot{m}_f + C_f\dot{m}_f^2\right)\right] \tag{5}$$

Equations of hydraulic lines:

$$\frac{\mathrm{d}\dot{m}_i}{\mathrm{d}t} = \frac{1}{\lambda}\left(p_1 - p_2 - \xi_i\frac{\dot{m}_i^2}{2\rho}\right) \tag{6}$$

where all of the symbols and the terminology are defined in the Nomenclature.

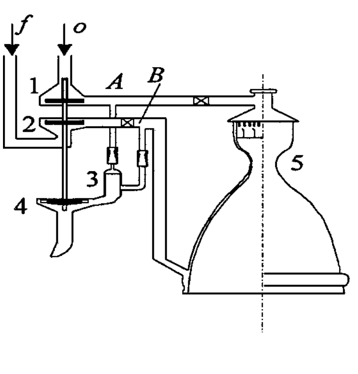

Fig. 1 Structure of rocket engine showing oxidizer pump, 1; fuel pump, 2; and combustion chamber, 5.

For Eqs. (1–6), we select some possible online detected parameters as the outputs of the engine and regard the pressures of propellant tank p_{oT} and p_{fT} as the inputs of the engine. Thereby the characteristics of the LRE can be established with a set of differential equations as follows:

$$\dot{\boldsymbol{x}}(t) = f[\boldsymbol{x}(t), \boldsymbol{u}(t), t], \qquad \boldsymbol{y}(t) = g[\boldsymbol{x}(t)] \tag{7}$$

If propellant leaks occurred in some segment of the hydraulic lines, the corresponding fluid resistance coefficients ξ_i will change. However, it is impossible to obtain the fluid resistance coefficients ξ_i by measurement. We can estimate the variation of the fluid resistance coefficients ξ_i by using methods based on joint state and parameter estimation. Thus, Eq. (7) can be modified as follows:

$$\dot{\boldsymbol{x}}(t) = f[t, \boldsymbol{x}(t), \boldsymbol{u}(t), \xi_i(t)], \qquad \boldsymbol{y}(t) = g[\boldsymbol{x}(t), \xi_i(t)] \tag{8}$$

Strong Tracking Filter

Making Eq. (8) discrete, considering the influence of noise, and regarding the fluid resistance coefficients as extended states, we can obtain

$$\boldsymbol{x}(k) = f[k-1, \boldsymbol{u}(k-1), \xi_i(k-1), \boldsymbol{x}(k-1)] + v(k-1)$$

$$\xi_i(k) = \xi_i(k-1), \qquad \boldsymbol{y}(k) = h[k, \xi_i(k), \boldsymbol{x}(k)] + e(k) \tag{9}$$

where $\boldsymbol{x}(\cdot)$ is an n-dimensional state vector, $\boldsymbol{y}(\cdot)$ is an r-dimensional measurement vector, $v(\cdot)$ is an n-dimensional process noise, and $e(\cdot)$ is an r-dimensional measurement noise. Suppose the characteristics of noise are

$$E[v(k)] = 0, \qquad E[(e(k)] = 0$$

$$E[(v(j)v^T(k)] = \delta_{jk}Q_1(k), \qquad \delta_{jk} = \begin{cases}1, & j = k\\ 0, & j \neq k\end{cases}$$
$$E[(e(j)e^T(k)] = \delta_{jk}Q_2(k),$$

Let

$$\boldsymbol{x}_e(k) = \begin{bmatrix}\boldsymbol{x}(k)\\ \xi_i(k)\end{bmatrix}$$

$$f_e[k, \boldsymbol{u}(k), \boldsymbol{x}_e(k)] = \begin{Bmatrix} f[k, \boldsymbol{u}(k), \xi_i(k), \boldsymbol{x}(k)]\\ \xi_i(k)\end{Bmatrix}$$

$$\times\, h_e[k, \boldsymbol{x}_e(k)] = h[k, \xi_i(k), \boldsymbol{x}(k)]$$

then Eq. (9) can be expressed as follows:

$$\boldsymbol{x}_e(k) = f_e[k-1, \boldsymbol{u}(k-1), \boldsymbol{x}_e(k-1)] + v(k-1)$$

$$\boldsymbol{y}(k) = h_e[k, \boldsymbol{x}_e(k)] + e(k) \tag{10}$$

We consider a linear Taylor approximation of the system function $f_e(\cdot)$ at the previous state estimate $\hat{\boldsymbol{x}}_e(k/k)$ and that of the observation function $h_e(\cdot)$ at the corresponding predicted position $\hat{\boldsymbol{x}}_e(k+1/k)$. Now we can design an extended Kalman filter according to the obtained linear model. When the model parameters do not entirely match the actual ones and the initial guess is suitable, the extended Kalman filter can converge to a reasonable estimate. However, if the normal process model is quite uncertain, the estimate accuracy of extended Kalman filter will decrease greatly and even will lead to instability.

To enhance the strong tracking ability of the filter, we can use a variable fading factor to adjust the prediction of the covariance matrix of states and the corresponding Kalman gain matrix. It is described by the following:

$$P(k+1/k) = \lambda(k+1)F[k, \boldsymbol{u}(k), \hat{\boldsymbol{x}}_e(k/k)]$$

$$P(k/k)F^T[k, \boldsymbol{u}(k), \hat{\boldsymbol{x}}_e(k/k)] + Q_1(k)$$

where $\lambda(k+1) \geq 1$ is a time-variant fading factor, which is used to eliminate the influence of previous data. The fading factor $\lambda(k+1)$

can be determined by the orthogonality conditions of the output residues. Detailed discussion of $\lambda(k+1)$ may be found in Ref. 6.

Because of the influence of model uncertainty, the estimated states of the filter will depart from the system states, and this behavior will be obviously exposed by the output residual errors. As long as we adjust the gain matrix $K(k+1)$ at real time to keep the residues' orthogonality, the filter will be forced to keep tracking the system states. Because the strong tracking filter has strong robustness to model uncertainty, we can use it for the joint nonlinear time-variant state and parameter estimate.

Therefore, the time-variant Kalman gain matrix $K(k+1)$ can also be determined.[6]

Leak Fault Detection of LRE

A. Strategy of Leak Detection

When the leak occurs, it will grow more and more serious. Therefore, it is necessary to detect the leak in time. Suppose the leak is a slow drift-type fault. It is described as follows:

$$\xi_i(k+1) = \xi_i(k) + D_\xi(k)$$

where $D_\xi(k)$ is the drift of $\xi_i(k)$ at the time point k.

While the engine is running at the normal state, $\xi_i(k)$ will satisfy the Gaussian distribution $\xi_i(k) \sim N(\xi_i^0, \sigma_{\xi_i^0}^2)$, where ξ_i^0 is the normal value of fluid resistance coefficient. As the leak occurs, it can be detected by the modified bias method. The modified bias method can be expressed as follows:

$$\mu_{\xi_i}(k) = \frac{1}{N_1}\sum_{j=1}^{N_1}\hat{\xi}_i\left(\frac{k-j}{k-j}\right)$$

$$\sigma_{\xi_i I}^2 = \frac{1}{N_1-1}\sum_{j=1}^{N_1}\left[\hat{\xi}_i\left(\frac{k-j}{k-j}\right) - \xi_i^0\right]^2 \quad \sigma_{\xi_i II}^2 = \frac{1}{N_1-1}\sum_{j=1}^{N_1}\left[\hat{\xi}_i\left(\frac{k-j}{k-j}\right) - \mu_{\xi_i}(k)\right]^2$$

$$d_{\xi_i}(k) = \frac{\sigma_{\xi_i I}^2(k)}{\sigma_{\xi_i^0}^2} - \ln\frac{\sigma_{\xi_i II}^2(k)}{\sigma_{\xi_i^0}^2} - 1, \qquad i = 1, 2, \ldots, l$$

where N_1 is the length of the data window.

When the engine is running at the normal state, d_{ξ_i} is close to zero. As soon as the leak occurs, d_{ξ_i} will increase rapidly. When a threshold β_{ξ_i} is defined, the strategy of leak fault detection is, thus, obtained,

$$d_{\xi_i}(k) \le \beta_{\xi_i}, \qquad d_{\xi_i}(k) > \beta_{\xi_i}$$

is the normal fault.

B. Numerical Simulation

Suppose the extent of the leak increase is according to the fraction exponent while the leak occurs,

$$\xi_i = \begin{cases} 1, & 0 < t < t_s \\ \xi_{i\,\max} - (\xi_{i\,\max} - 1)\cdot\exp[-kf(t - t_s)], & t > t_s \end{cases}$$

where t_s is the time the leak occurs and $kf = 0.2{-}0.5$ is the fraction exponent.

We have to select the online measuring parameters as the outputs while applying the approach to the engine. However, to do the research, we select the parameters as follows:

$$x_e = \{p_c, r_c, p_b, r_b, n, m_o, m_{oc}, m_{ob}, m_f, m_{fc}, m_{fb}, \xi_{om}, \xi_{og}, \xi_{fm}, \xi_{fg}\}$$

$$y = \left\{p_c, p_b, n, m_o, m_f, p_o^l, p_f^l, p_{oi}, p_{if}\right\}$$

In the simulation, all of these parameters are expressed in unitary form.

It is unavoidable for the system to have a process noise of high frequency because the LRE is a strong coupling and nonlinear system, and it often runs when the situation is serious. The inertia of the LRE mainly focuses on the turbopump component, and the rotor equation of the turbopump describes the property of mean speed. Therefore, the process noise can be neglected. The influence of the process noise on the other components, however, has to be considered.

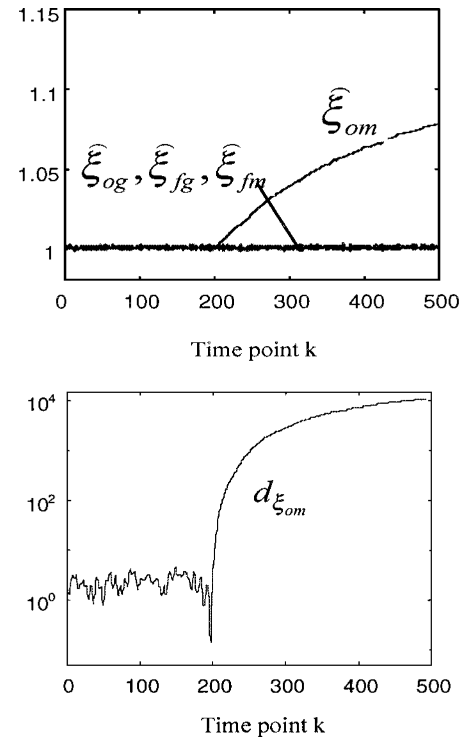

Fig. 2 Leak occurring between the oxidizer offset (position *A*) and combustion chamber.

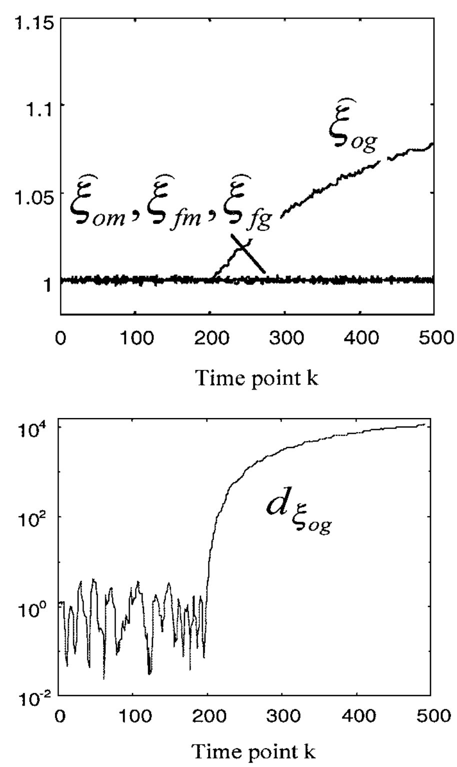

Fig. 3 Leak occurring between the oxidizer offset (position *A*) and gas generator.

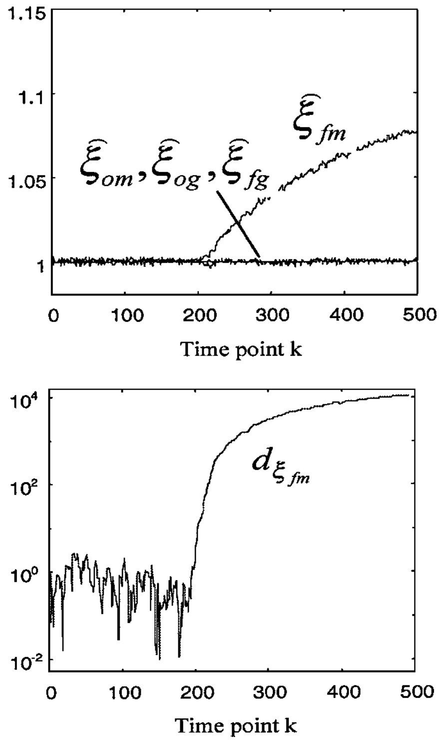

Fig. 4 Leak occurring between the fuel offset (position B) and combustion chamber.

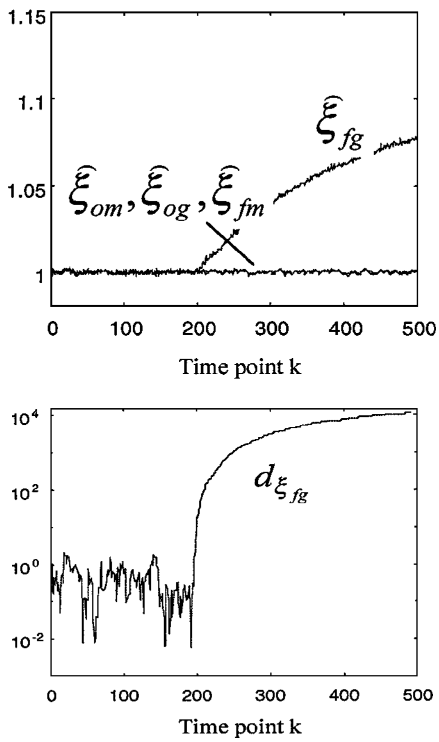

Fig. 5 Leak occurring between the fuel offset (position B) and gas generator.

In the simulation, the initial values of the strong tracking filter are given as follows:

$$Q_1 = \text{diag}(0.001, \ldots, 0.001)_{15 \times 15}$$

$$Q_2 = \text{diag}(0.001, \ldots, 0.001)_{9 \times 9}$$

$$P = \text{diag}(0.01, \ldots, 0.01)_{15 \times 15}$$

Figure 2 shows the results of the leak occurring between the oxidizer offset (position A) and the combustion chamber. From Fig. 2, we know the corresponding estimated fluid resistance $\hat{\xi}_{om}$ is variable, but the others are not changed at time point $k = 200$. This phenomenon shows that the leak occurs on this hydraulic line. We also can see $d_{\xi_{om}}$ increases rapidly. If we select the threshold $\beta_{\xi_{om}} = 10$, the leak can be detected at time $k = 203$.

Some other simulations for the other possible leak situations are carried out, and the results are given in Figs. 3–5. It can be seen from Figs. 3–5 that whenever leaks occurred in the hydraulic line, the corresponding fluid resistance coefficients change significantly from their normal values and the estimated fluid resistance $d_{\xi_{om}}$ change rapidly, too. These phenomena show that the hydraulic leak occurs in the corresponding hydraulic line. By the suitable selected threshold, we can detect when and where the leak occurred.

Conclusions

Because the reliability of the LRE is becoming more and more important, and the leak is one of the most common faults of the engine, it is necessary to investigate further the leak fault of LRE.

Because a strong tracking filter has the merit of strong robustness to actual parameter perturbation and strong tracking of the jumping states, as well as tracking the drifting states even with the filter being stable, it is especially suitable for joint state and parameter estimation. A strong tracking filter is used to estimate the fluid resistance coefficients in this paper. According to the estimated fluid resistance coefficients, the leak can be detected. The simulating result shows that it is feasible.

Acknowledgment

This work was supported by the Chinese Space Flight Fund Grant 960241049.

References

[1] Hammock, W. R., Jr., Cota, P. E., Jr., Rosenbaum, B. J., and Barrett, M. J., "Investigative Techniques Used to Locate the Liquid Hydrogen Leakage on the Space Shuttle Main Propulsion System," AIAA Paper 91-1936, June 1991.

[2] Ali, M., and Gupta, U., "An Expert System for Fault Diagnosis in a Space Shuttle Main Engine," AIAA Paper 90-1890, July 1990.

[3] Wu, J. J., Zhang, Y. L., Chen, Q. Z., and Huang, M. C., "Fault Detection and Diagnosis Based on Neural Networks for Liquid Rocket Propulsion System," AIAA Paper 95-2350, July 1995.

[4] Walker, B., and Baumgartner, E., "Comparison of Nonlinear Smoothers and Nonlinear Estimators for Rocket Engine Health Monitoring," AIAA Paper 90-1891, July 1990.

[5] Maram, J. M., "Remote Rocket Engine Leak Detection Techniques," AIAA Paper 95-2645, June 1993.

[6] Zhou, D. H., Xi, Y. G., and Zhang, Z. J., "Suboptimal Fading Extended Kalman Filter," *Proceedings of the ASME International Conference on Signals and Systems*, Vol. 4, American Society of Mechanical Engineers, Fairfield, NJ, 1990, pp. 1–10.