Data Systems and Data Analysis Methods to Support Onboard In-Flight Operations

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In aircraft or spacecraft operations, it is desirable for safety and economic reasons to monitor continuously the condition of critical vehicle systems such as engines, controls, nagivation, etc. Currently, onboard systems to accomplish in-flight monitoring and checkout are gaining acceptance, and are being used more widely in aircraft and spacecraft. As the capability and capacity of onboard hardware for in-flight monitoring improves, more elaborate analytical methods may be employed for data processing. As an example, this paper suggests how some postflight data analysis methods for launch vehicle evaluation may be used within an onboard in-flight checkout system. A concept is proposed for an integrated data processing system using modifications to existing techniques, to permit near-real-time fault detection, isolation, diagnosis, and prediction. The emphasis is on sequential processing on only out-of-tolerance data. The approach is to reduce continually the amount of data to be processed, on the basis of whether additional information can be gained from the next processing step. Recommendations are given for further work necessary to develop and implement the concept to permit onboard in-flight monitoring of critical systems.

Introduction

TYPICAL data systems to support manned operations are described in the literature. As an example, a review of different but closely related aspects of manned operations support includes such subjects as automatic test and check out for launch vehicle countdown,[1] onboard in-flight checkout for spacecraft or aircraft,[2] air route traffic control for aircraft,[3] and mission control for spacecraft.[4] The importance of efficient data monitoring and processing, coupled with appropriate displays, facilities, and personnel for control is apparent in a review of this sort. Two major conclusions are indicated. 1) Adequate hardware and technological developments exist for data monitoring, data acquisition, data display, and system control. 2) Much research and development effort is required to improve data analysis methods. The second conclusion is especially significant regarding onboard in-flight monitoring and processing. It is pointed out that detecting, diagnosing, and predicting faults in propulsion systems have met with limited success; and, for nonpropulsion systems, present data analysis techniques are barely adequate for fault isolation, with almost no application to failure prediction.[2] This paper is devoted to improvements in analytical methods for detecting, diagnosing, and predicting faults in flight vehicle systems. It draws upon some techniques developed for Lunar Orbiter and Saturn V launch vehicle postflight evaluation. These techniques are for data compression, automated inspection of telemetry data, and optimal estimation of vehicle performance parameters.

The data compression techniques considered here are the same as used in existing orbit determination programs. In these programs, a radar doppler "integrated count" (in essence, a compression) is differenced with a corresponding set of compressed data values for the predicted or nominal observations. These residuals are used in the trajectory estimation program to determine the lunar probe flight path.[5,6] The data compression method preserves all the usable information of the measurements and is general so that it may be used to process any type of data. How this may be applied to the particular problem at hand is discussed later.

The postflight data inspection methods for application herein are based upon the automated telemetry data inspection program (ATI) developed for the Saturn V launch vehicles.[7] Within a few hours after each Saturn V flight, it is used to identify potential vehicle problem areas quickly. The program is illustrated in Fig. 1 and functions as follows.

Prior to launch, predicted information for all telemetry measurements are obtained. This information includes 1) the expected value of each measurement vs time, with a band indicating high and low tolerances about the nominal, 2) a measurement correlation matrix indicating which measurements have a strong physical correlation, and 3) instrumentation measurement number, type, range, units, etc. All of this information is processed and stored on magnetic tape for comparison with the postflight data.

The ATI program outputs are 1) a summary listing of measurement out-of-tolerance conditions and the average percent each measurement is out of tolerance, 2) a correlation-results listing giving, for each out-of-tolerance measurement, a list of all other correlated measurements that are also out of tolerance, with all out-of-tolerance time periods indicated, 3) for each out-of-tolerance measurement, a listing of the parameter value vs time, and 4) a plot of each out-of-tolerance measurement vs time. An example of the latter output is shown in Fig. 2. The capability of the ATI computer program to support manned operations should be apparent since it is the basic type of tool required to provide prediction, failure identification, and fault isolation information.

The parameter estimation methods suggested for this work are also from a program developed for Saturn V postflight analysis.[8] The program, which utilizes flight data (or data derived from flight data), determines an optimal estimate of certain performance parameters of the Saturn V launch vehicle. These parameters, some of which cannot be measured directly, include individual engine thrust, aerodynamic forces, initial mass, and rate of change of total vehicle mass. The program functions as follows.

The vehicle performance parameters of thrust, mass flow rate, initial mass, and aerodynamic forces are computed from separate analysis programs that use telemetry flight data as inputs. These are the reference values for the parameter estimation program and are used in the right-hand side of the

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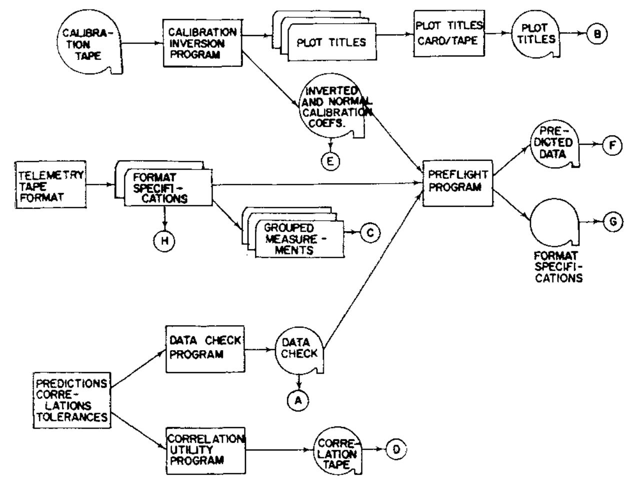
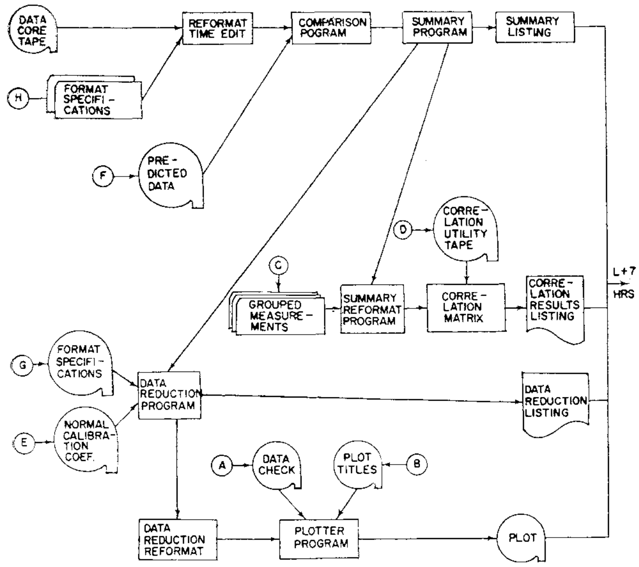


a) **Preflight data preparation**



b) **Postflight data processing**

Fig. 1 Automated telemetry inspection program.

simple equation $a = \Sigma(F/M)$. The acceleration term of the equation is determined from tracking and guidance telemetry data.[9,10] In general, there is not agreement between the right- and left-hand sides of the equation. Through the application of optimal estimation methods, the performance parameters are established so that agreement with the measured trajectory is obtained. The functional operation of the parameter estimation program is as indicated in Fig. 3. Typical results from a Saturn V flight are shown in Fig. 4.†

The methods of the parameter estimation program can be applied to other data sets to obtain performance estimates of

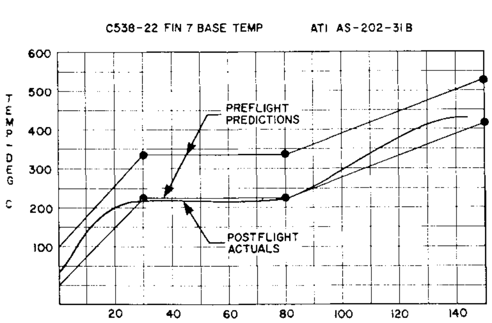


Fig. 2 Typical automated telemetry inspection results.

† Synthetic flight data were used here since actual Saturn V flight data were not available at the time this paper was prepared.

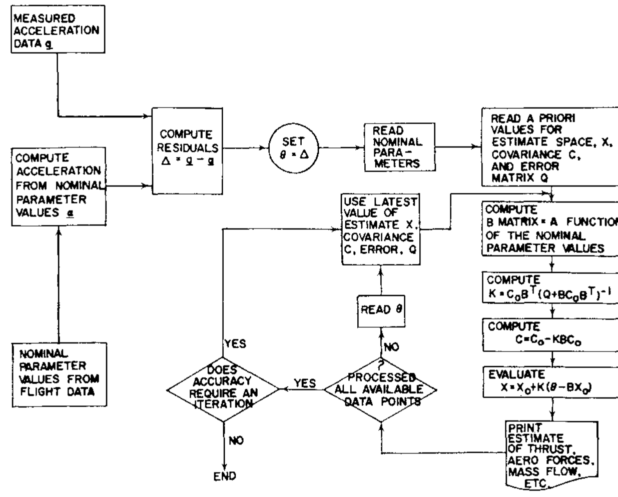


Fig. 3 Parameter estimation program.

vehicle individual systems such as engines, controls, etc. The program operates sequentially and hence is easily adaptable to a real-time or near-real-time function. Modified in this fashion, the performance estimation program may be used as a trend analysis routine for monitoring vehicle systems' in-flight performance. The next section will show how these data systems and analysis methods have a real-time capability, and can be extended to support manned operations.

Support to Manned Operations

A typical illustration of support for manned flight operations is shown in Fig. 5.[4] The block diagram portrays the over-all decision logic required, and a key element of this network is the diagnosis of vehicle systems. This aspect of support to manned operations is now treated in detail. The emphasis is upon the definition of an efficient onboard data processing system for near-real-time in-flight monitoring.

Vehicle Systems Diagnosis

The processing of data for systems diagnosis is illustrated in Fig. 6. It is a typical representation of the steps for onboard or ground-based processing of data from monitored vehicle flight systems.[2] The routines discussed earlier in this paper may be incorporated within such a data processing system as follows.

Data editing and checking

The data-editing routine checks for errors, performs data conversions, reformatting, etc. Since such routines are fairly common, it is not discussed in detail here, but it is recognized as an important link in the total processing chain of events.

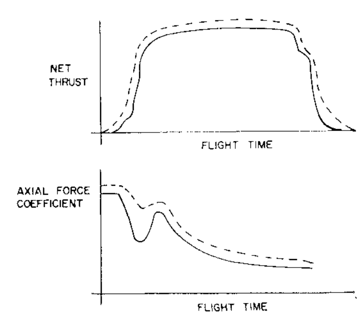


Fig. 4 Typical results, vehicle performance parameter estimation; --- postflight data,—— postflight best estimate.

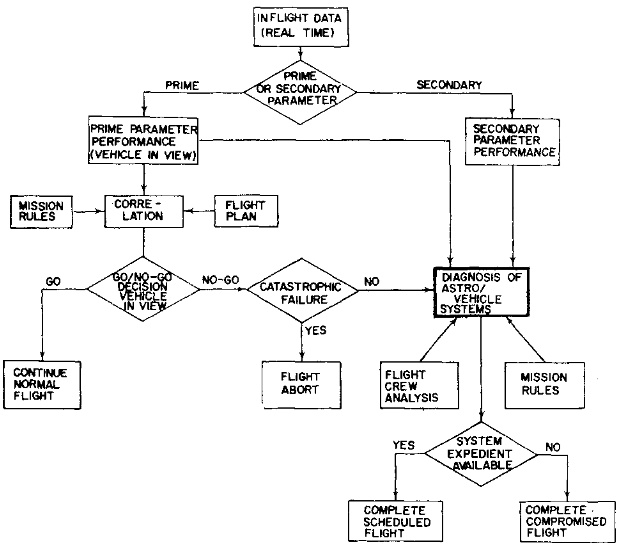


Fig. 5 Decision logic for manned flight operations (typical).[4]

Data compression

The processing of a minimum amount of the monitored flight data to accomplish systems diagnosis is essential for an onboard near-real-time application. Data compression is one expedient in achieving this goal. This can be handled through the application of any one of several schemes. The method used here is based on a power series expansion of the mathematical model of the actual data, without noise, about the midpoint of the data span for compression.[5] The expression, using only the first two terms of the expansion is

$$\chi = X(t_m) + [(\tau^2 - \Delta t^2)/24]\,\ddot{\chi}(t_m)$$

where χ is the value of the compressed data, $X(t_m)$ is the theoretical data value at the midpoint of the data over the time span τ, $\ddot{\chi}(t_m)$ is the second derivative of the data evaluated at t_m, the time corresponding to the data point at the midspan, and Δt is the constant data-sampling interval. The actual data are then summed and compared to the theoretical sum to form a residual. This scheme reduces the number of data points to be processed but retains all the usable information of the data. Compression ratios are a function of the data type but may be on the order of 100 to 1.

The data compressor sequentially processes all the data from the vehicle measuring system. The logic and computing times are dependent upon the system hardware, the number of variables m being monitored, definition of critical systems, etc. Data compression is illustrated in Fig. 7. In examining a given variable, the ith, a data arc is selected, the kth, and a nominal compressed data value χ_{ijk} is determined which contains all the information within the data arc. This value χ_{ijk} is the kth value within the jth sample set, S_{ij}, of the ith variable. The manner in which the compressed data values χ_{ijk} of the sample set S_{ij} are used in the next processing step is discussed within the fault detection routine.

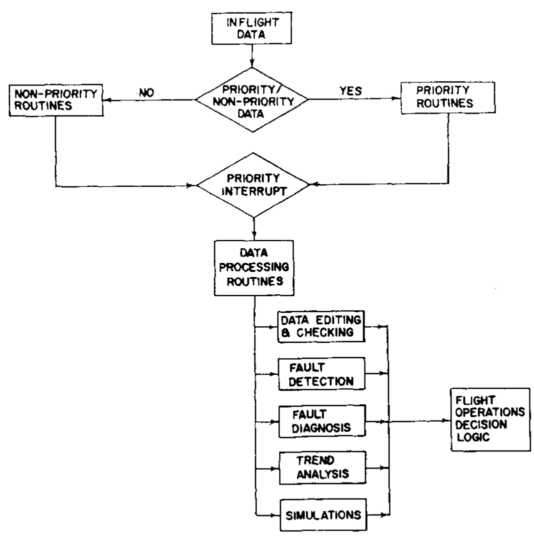


Fig. 6 Data processing for systems evaluation (typical).[2]

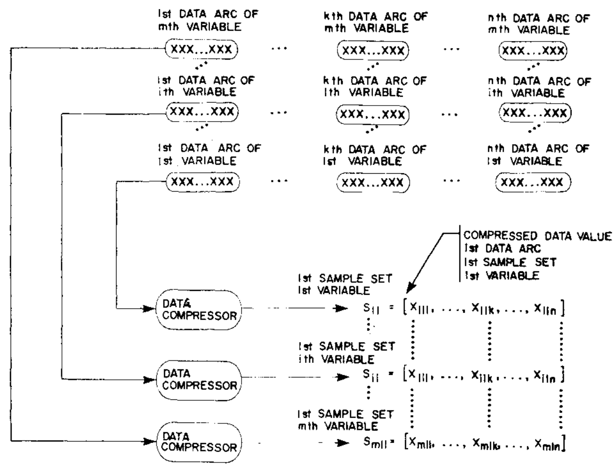


Fig. 7 Data compression processing.

Fault detection and trend analysis

The comparator routine of the automated telemetry data inspection program is a type of fault detection.[7] A high/low limit comparison and an out-of-tolerance persistency check are made. This identifies a variable that is out of tolerance for a period of greater than some specified time. A variation of this method is used for the fault detection routine within the present program. This is illustrated in Fig. 8.

The n compressed data values χ_{ijk} of the sample set S_{ij} are entered into the routine. The difference between the mean value of the variable μ_i and the first compressed data value χ_{ij1} is compared with three times the standard deviation $3\sigma_i$ of the variable. If the difference is greater than $3\sigma_i$, the count register C_{ij} records one count. The processing continues for all n compressed data values of the sample set. If the count register C_{ij} does not exceed a given number Q_{ij}, all of the processed data are within the expected range and are discarded. If C_{ij} does exceed Q_{ij}, the information is used from the histogram, which is computed in parallel with the foregoing processing steps.

The histogram is a part of the quantile routine, which is a statistical method for calculating the mean and variance of a data sample set.[11] The histogram is constructed from recordings of the number of times a given percent out-of-tolerance condition exists vs the percent out-of-tolerance range. The statistical measures, or quantiles, determined from the histogram are used to compute the new mean and variance for the sample set S_{ij}. The number of quantiles required for this computation is small. Therefore, if n the number of the compressed data values χ_{ijk} within the sample set S_{ij} is large, the quantiler functions as a further data compression device.

The new values of the mean and standard deviation as determined by the quantiler are the basis for fault detection and trend analysis. A new mean μ_{ij} indicates a persistently out-of-tolerance condition greater than $3\sigma_i$ for the ith variable over the time span for the sample set. If this out-of-tolerance condition recurs over several sample sets of the variable, a trend is indicated.

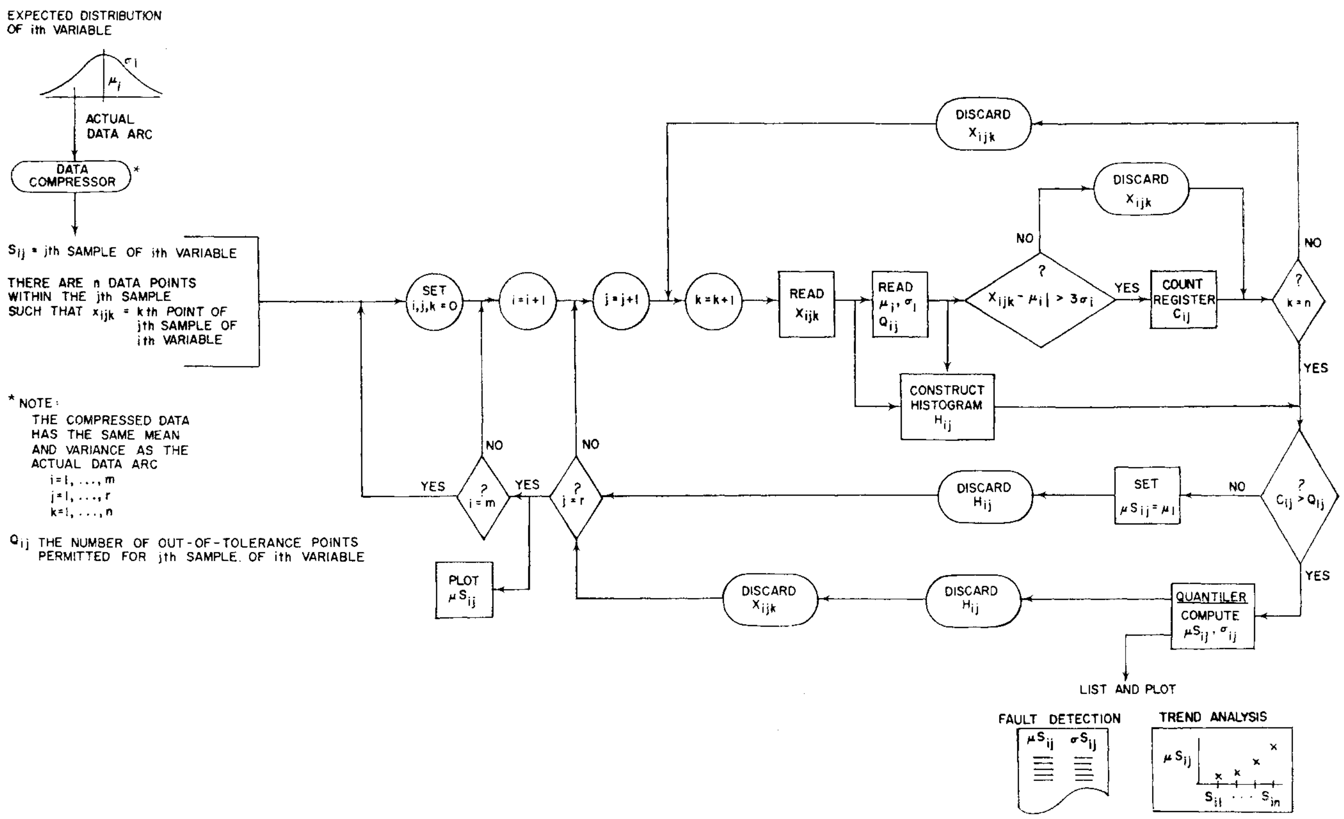


Fig. 8 Fault detection and trend analysis.

The fault detection and trend analysis routine provides information which indicates potential problems. Nothing more is concluded at this point since the results are for the individual variables, $i = 1, \ldots, m$, and the sample set intervals, $j = 1, \ldots, r$. Further information is available from this collection of out-of-tolerance data by noting what physical correlation these variables have one to another. Such is the function of the next data processing step, the correlation routine.

Out-of-tolerance variable correlation

The correlated measurements routine of the automated telemetry data inspection program is reviewed in earlier sections. Modifications to this routine result in the out-of-tolerance variable correlation routine within the present program. The basic logic of the correlation routine is contained within the correlation matrix. This is a yes/no test of each out-of-tolerance variable with all the other variables. A "yes" indicates there is a strong physical correlation between variables χ_1 and χ_2; "no," that there is not. The correlation test continues to the next logic step, which identifies, for those variables out-of-tolerance and correlated, when they first went out of tolerance and when they returned within tolerance. The final step in the correlation routine lists the correlated variables sequenced according to the time each went out of tolerance. The correlation routine is illustrated in Fig. 9.

The information from the correlation routine, coupled with the fault detection and trend analysis results, provide the basic information required for fault isolation and diagnosis. Also, since correlated out-of-tolerance variables are generally from measurements of a particular system, such as engines, controls, etc., this information permits the identification of which systems should be analyzed for fault prediction.

Fault prediction

Prediction of a failure requires information from several measured variables that collectively provide information about a complete system. Methods of the parameter estimation program discussed previously may be used to provide failure prediction information. As an example, consider fuel flow rate $\dot{\omega}_f$ of a rocket engine. Typically, there is a direct correlation between $\dot{\omega}_f$ and several other variables, such as pump-inlet pressure P_i, pump rpm n_s, pump-discharge pressure P_d, and engine-chamber pressure P_c. This relation may be expressed as

$$\dot{\omega}_f = f(p_i, n_s, p_d, p_c)$$

Now, it may be assumed that measured variable of some of these parameters are available from instrumentation of the monitoring system. In this example, measured or measurement-derived values of pump-inlet pressure, rpm, pump-discharge pressure, and engine-chamber pressure are assumed to be the reference data. Through the methods of the parameter estimation program, fuel flow rate data are introduced and processed to determine an optimal estimate of the reference data. This information is consistent from a physical point of view, as described by the previous expression; and, as an additional output from the parameter estimation program, a new and consistent set of values for the standard deviations of the reference data is available. These results from the parameter estimation program may be used to confirm the answers from the fault detection, trend analysis, and correlation routines. This confirmation frequently is enough to

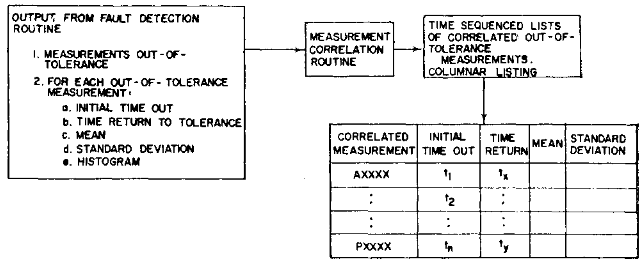


Fig. 9 Information for fault isolation diagnosis.

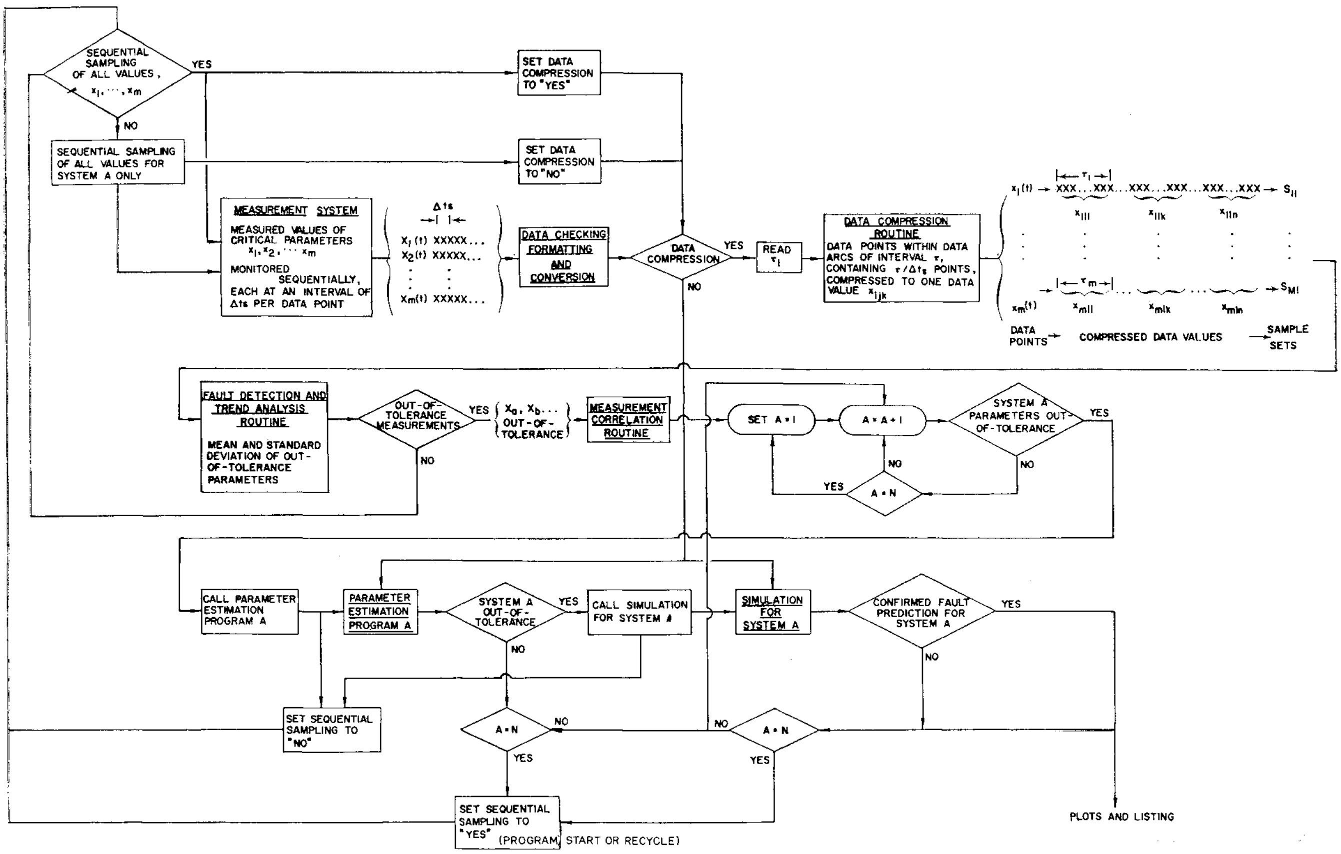


Fig. 10 Integrated data processing system for onboard inflight monitoring (conceptual).

predict system failure. However, at this step in the processing chain of events, it may be possible to introduce a more complicated nonlinear mathematical simulation of the suspected system.

Simulation

A final step in the processing of data for onboard in-flight monitoring of critical systems is simulation. This would be used only after the preceding steps have isolated a particular system and given confirming information that the system is probably malfunctioning. Such a simulation, coupled with appropriate logic, would function in near-real-time and utilize the corresponding measured data, in uncompressed form, as inputs. The results from the simulation would be used as final and conclusive proof of pending system failure.

Integrated Data Processing System

The preceding section presented some data processing details for fault identification and diagnosis of vehicle systems. The coupling of these routines to form an integrated system for onboard in-flight monitoring is now discussed. There are many ways this might be accomplished, but the concept suggested here, as illustrated in Fig. 10, conveys the basic idea. Throughout it is assumed that the computer, peripheral hardware, and associated software are adequate to provide the necessary buffers, core storage, data manipulation, logical flow, etc. Consequently, these functions will not be considered here. The data processing events are as follows.

Initially, the measuring system is set to sample sequentially the measured values of all the parameters $\chi_1, \chi_2, \ldots, m$. The data flow is then through the data compression, fault detection, and trend analysis routines. If no measurements are out of tolerance, the data processed thus far are discarded and processing of the next sampling set begun. If some parameters indicate out-of-tolerance conditions, processing continues through the measurement correlation routine. The correlated out-of-tolerance measurements are grouped according to the vehicle system with which they are associated, such as system A, system B, . . ., system N.

If a given number of the measured parameters of system A are out of tolerance, the processing logic switches the data flow. This causes data from the measuring system to bypass the data compression routine, etc., and be put directly into the parameter estimation program for system A. If results of the parameter estimation program indicate system A to be out of tolerance, the processing logic calls for the simulation program for system A, also with data input directly from the measuring system. Here, fault prediction for system A is confirmed, or invalidated, and the processing continues to check the remaining out-of-tolerance parameters and systems. Following this, the entire processing system is reinitialized, and the cycle is begun again.

Conclusions and Recommendations

The ideas presented in the preceding sections suggest a concept for near-real-time fault detection, isolation, diagnosis, and prediction. To develop and implement this concept to permit onboard in-flight monitoring of critical systems requires a significant extension of this and related work. Some of these necessary extensions are now considered.

System Design

A successful in-flight monitoring system will evolve from an integrated design and development program. The design must consider both hardware and software capabilities for data monitoring, acquisition, processing, and display. The design should recognize and consider such things as:

1) The minimum number of parameters that, if monitored, could describe the performance of a system.

2) The type of instrumentation to measure these parameters.

3) The analytical methods to compute information or parameters that are unmeasurable.

4) The form of the data to be processed (analog or digital).

5) The sampling rate for digitized data.

6) The type and capacity of hardware for analog data processing and digital data processing.

7) The logic to permit priority and nonpriority processing, automatic modes, manual interrupt modes, etc.

8) The need for system redundancies and self-checking.

9) The definition and number of critical systems to be monitored.

10) The analytical models to describe or simulate performance of critical systems.

There are other considerations, too, but the preceding ones are enough to stress the importance of an integrated system design approach. This would be different for each particular application—aircraft, spacecraft, etc.—and would undoubtedly be tailored to satisfy best the needs of each. As an example, the analytical methods presented in this paper must be defined very specifically, especially the parameter estimation programs and the simulations. Much engineering analysis and computer program development work would be required to assure that such programs are 1) adequate mathematical models of the physical systems they represent, 2) efficient from a computing point of view and able to operate in near real time, and 3) reliable and accurate in determining system performance and predicting failures. These points, especially the latter, are emphasized and elaborated upon in the literature.[12] In addition, a great deal of engineering analysis would be required to establish the size of a data sampling set and effectiveness and efficiency of the data compression, fault detection, trend analysis, and correlation routines. Finally, new analytical methods most probably are required for certain types of data, such as vibration and acoustic measurements. Results from such information may be more efficiently derived from analog methods and analog computing equipment.

System Development and Implementation

The development and implementation of the onboard inflight monitoring systems involves considerable time and expense. This is obvious from a review of the work which has been accomplished to date.[2,12] It requires the design, manufacture, procurement, installation, test, and checkout of necessary hardware for a given flight vehicle. Coupled with this is an extensive flight test program for verification and operational acceptance. Here too, the software developments, as typified by the analytical methods described in this paper, would be subject to special scrutiny, since inflight operational demands may place requirements and constraints upon the software which were not anticipated in the original engineering definition phase.

Concluding Remarks

In this paper, a concept has been presented for an integrated onboard in-flight data processing system for near-real-time fault detection, isolation, diagnosis, and prediction. It was shown how related methods from launch vehicle, spacecraft, and aircraft activities were modified, extended, or applied to the development of this system. The special details and features of the major routines for onboard monitoring were elaborated upon and a discussion of how these separate routines may be integrated into a complete and efficient data processing system was given. Recommendations were made for what must be done to extend these concepts, through more complete system design, development, and implementation, in order to permit effective onboard in-flight monitoring of critical systems.

As a closing comment, it would seem quite clear that much remains to be done before a truly effective and operational inflight monitoring system is available for aircraft or spacecraft. However, the need for such a system is great, and will become increasingly so as more aircraft or spacecraft of increasing complexities enter service and as the space program matures, bringing about multiple missions of very long duration.

It is hoped that continuing efforts will soon lead to the successful development of an onboard in-flight monitoring system; and that the ideas presented herein may contribute to this development, and hence, to improvements in the safety of manned flight operations.

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