JOURNAL OF SPACECRAFT AND ROCKETS
Vol. 29, No. 1, January–February 1992

Interpolation/Extrapolation Technique with Application to Hypervelocity Impact of Space Debris

William Keith Rule*
University of Alabama, Tuscaloosa, Alabama 35487

A new technique for the interpolation/extrapolation of engineering data is described. The technique easily allows for the incorporation of additional independent variables, and the most suitable data in the data base is automatically used for each prediction. The technique provides diagnostics for assessing the reliability of the prediction. Two sets of predictions made for known 5-degree-of-freedom, 15-parameter functions using the new technique produced an average coefficient of determination of 0.949. Here, the technique is applied to the prediction of damage to the Space Station from hypervelocity impact of space debris. A new set of impact data is presented for this purpose. Reasonable predictions for bumper damage were obtained, but predictions of pressure wall and multilayer insulation damage were poor.

Nomenclature

D = estimated value of dependent variable at an interpolation point
D_i = value of dependent variable at ith data point
D_p = diameter of projectile
M = number of data points in data base
N = number of independent variables
R_i = distance from ith data point to interpolation point
$rn\#$ = random number used to generate test function
S = length of influence of a data point
T_b = bumper thickness
T_{pw} = pressure wall thickness
V = projectile velocity
$x_{j,i}$ = jth coordinate of ith data point
$x_{j,\mathrm{INT}}$ = jth coordinate of interpolation point
θ = weighting factor of a data point
ϕ = impact angle

Introduction

THERE are many engineering applications in which predictions of the behavior of a physical system must be made based on a data base of experimental results. In these instances, either the phenomenon is too complicated to treat analytically or numerically, or the funding, expertise, or time required to do so is not available. Empirical approaches of this nature have always played a fundamental role in engineering design.

The usual procedure for making predictions from experimental data is to assume some form for the equation relating the independent variables to the dependent variable. The equation typically contains empirical coefficients, the values of which are determined from a fit to the experimental data.[1-6] The method of least squares is an example of a popular technique for obtaining the coefficients from the experimental data. The final result is a closed form equation for making predictions.

This approach has been found to work very well for many engineering applications; however, there are some disadvantages. A suitable form for the prediction equation must be developed. This is often difficult. Incorporating additional independent variables in an existing equation can pose problems. Usually, a well-defined procedure for taking into account new experimental data is not put in place. Generally, a single set of empirical coefficients is used to make predictions over a fairly wide range of values of the independent variables. Thus, the best data in a data base for making a prediction with a particular set of independent variables may not be used to best advantage. Also, it is usually difficult to assess the accuracy of the prediction.

This paper proposes a new method for making empirical predictions based on experimental data. The method uses a very general form of the prediction equation that can be applied in the same manner to all problems. Thus, the user is not required to develop a suitable form for the prediction equation, and additional independent variables can be easily incorporated. The new method is designed to work off of a data base that can be continuously updated as new experimental data become available. The method automatically takes advantage of the most appropriate data in the data base for a given set of independent variables. The method provides diagnostics for assessing the accuracy of the prediction.

This new technique was developed to predict the effects of hypervelocity debris impacts on the Space Station. The goal was to make quick, reliable predictions of impact behavior for trade studies based on a small set of experimental data. The new interpolation/extrapolation technique will be demonstrated for this application. A 16 MHz, 80386-based microcomputer was adequate for performing the calculations.

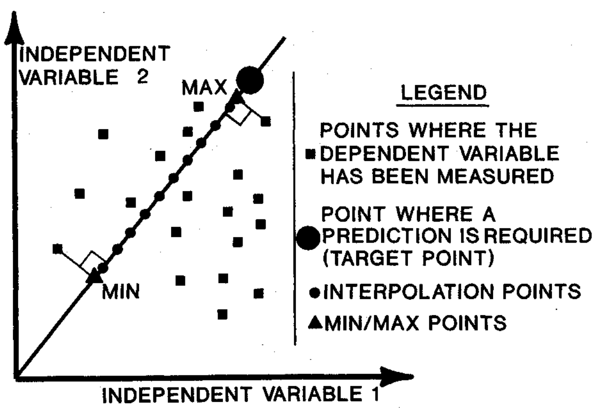

Fig. 1 Technique for selecting interpolation point locations for the case of two independent variables.

Received June 2, 1990; revision received Dec. 13, 1990; accepted for publication Dec. 18, 1990.

*Assistant Professor, Department of Engineering Mechanics. Member AIAA.

Description of the New Interpolation/Extrapolation Technique

In this section the procedure for using the new technique will be described. The technique has four main steps.

Step 1. Normalize the Independent Variables

In general, the independent variables will vary greatly in magnitude. In hypervelocity impact work, for instance, dimensions can be of order 10 and velocities of order 10^6. The new technique requires that all variables be of the same order of magnitude. This was accomplished by scaling the independent variables such that their mean value is equal to unity. Other scaling methods could, perhaps, be used to improve the accuracy of this technique. For instance, the variables could be scaled such that predicted values of points in the data base more closely match the measured values. This scaling technique was not tested. The dependent variables need not be scaled.

This technique works off of a data base that can and should be kept updated with the latest experimental data. Thus, the scaling factors will change as time progresses and the size of the data base increases.

Step 2. Select a Series of Points in the Data Domain for Interpolation

Two general requirements for prediction schemes are that the method should be capable of smoothing the data to cancel out, one hopes, the random scatter typically present in experimental measurements, and that the technique should allow for making reliable predictions outside of the domain of the measured data. Here, these requirements are satisfied by using the data to make 10 interpolations from within the domain of the data, which are then used for predicting the dependent variable at some point of interest. The 10 "interpolation" points should provide for sufficient smoothing of the data, and should also capture the trend characteristics of the data for extrapolation purposes, if an extrapolation is required. The number of interpolation points to use was selected on the basis of trial and error. Note that in some cases extrapolation can produce misleading results regardless of the extrapolation technique used.

Figure 1 provides an illustration of how the interpolation points are selected for a hypothetical case with two independent variables. An identical approach is used for the case of an arbitrary number of independent variables. In Fig. 1, the independent variables are in the plane of the page, and the dependent variable takes the form of a surface out of the plane of the page.

First, a "prediction" vector is drawn from the origin through the point in the domain, called the "target" point, where a prediction of the dependent variable is required. Then the "min" and "max" points (Fig. 1) are located on the prediction vector by considering the intersection points of

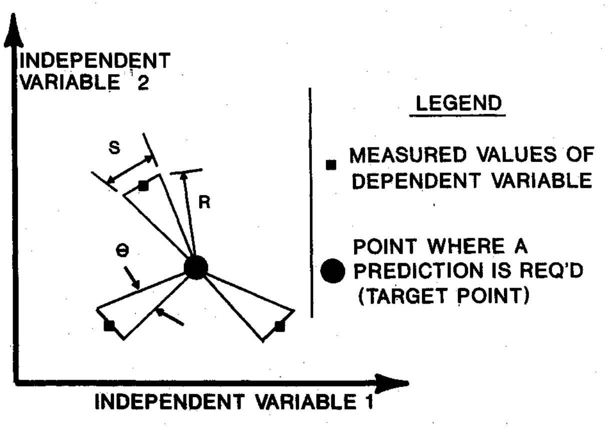

Fig. 2 Interpolation scheme for equally spaced data points.

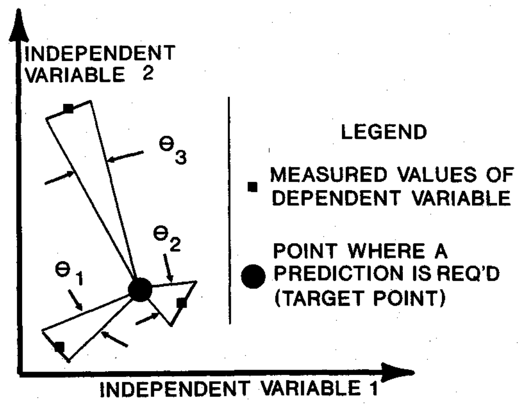

Fig. 3 Interpolation scheme for unequally spaced data points.

perpendiculars from the data points to the prediction vector. The closest intersection point to the origin defines the min point, and that of the farthest, the max point. Ten equally spaced points (interpolation points) on the prediction vector between the min and max points are then used for the next step in the prediction process. If the target point lies between the min and max points, then an interpolation is required; otherwise, an extrapolation is required.

Step 3. Estimate Values of the Dependent Variable at Interpolation Points

Next, values for the dependent variable must be estimated at the 10 interpolation points. This is done as indicated in the following equation:

$$D = \frac{\sum_{i=1}^{M} \frac{D_i}{R_i^{N-1}}}{\sum_{i=1}^{M} \frac{1}{R_i^{N-1}}} \tag{1}$$

The R_i are determined by the usual formula for determining the "distance" between two points in a multidimensional space:

$$R_i^2 = \sum_{j=1}^{N} (x_{j,i} - x_{j,\mathrm{INT}})^2 \tag{2}$$

The need for scaling the independent variables is evident from considering the form of Eq. (2).

The form of Eq. (1) will now be considered. It is assumed that, if all measured data points are the same "distance" R from an interpolation point, then all the measured data should be given equal weight. This situation is illustrated for the case of two independent variables ($N = 2$) in Fig. 2. This can be interpreted as saying that each data point has some "characteristic length of influence" S that subtends an angle $\theta = S/R = S/R^{N-1}$, as indicated in Fig. 2. The θ can be taken as the weighting factor. For the constant R case shown in Fig. 2, all data points would be given the same weight. Figure 3 illustrates the case for which the data points are considered to be equally valid (same S), but are located different "distances" from the interpolation point. Here, the weighting factors will be of the form $\theta_i = S/R_i^{N-1}$, and, thus, data points closer to the interpolation point will be given a higher weight. The value of the dependent variable at the interpolation point can be estimated from $D = \Sigma\theta_i D_i/\Sigma\theta_i$, which leads to Eq. (1). Note that a value for S is not required, as it cancels out of the equation.

The three-dimensional (three independent variables) application of this procedure leads to equations identical in form to those used for determining view factors in the field of radiation heat transfer.[7] The method described herein can be interpreted as though the measured data points are "radiating" information to the interpolation point. The farther away the

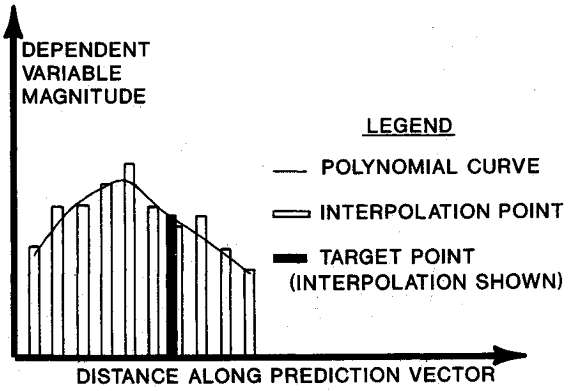

Fig. 4 Schematic of prediction reliability diagnostics.

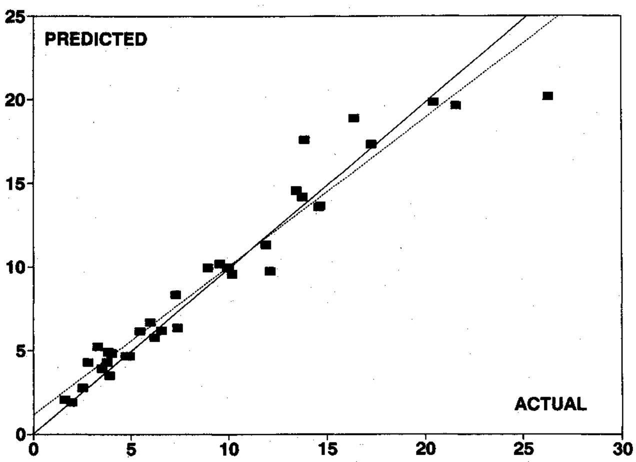

Fig. 5 Plot of actual vs predicted values using consistent data.

data point is, the weaker the "radiation" (lower weight given to the information). In principle, the method can easily be extended to any number of independent variables N.

Step 4. Fit a Polynomial Through the Interpolation Points and Make Prediction

The final step in the process involves fitting a polynomial through the 10 interpolation points, and then using the polynomial to make a prediction of the dependent variable at the target point. The polynomial describes how the dependent variable behaves as a function of distance along the prediction vector. By trial and error, it was found that a fourth-order polynomial worked well. The polynomial could be used for interpolation or extrapolation, depending on the location of the target point. There would, of course, be considerably more uncertainty in the prediction for the case of extrapolation. Errors in the 10 interpolation points tend to get smoothed by the polynomial.

Reliability Diagnostics of the New Interpolation/Extrapolation Technique

The method proposed herein provides diagnostics to help assess the accuracy of the prediction. The computer program can provide the user with averages of the independent variables of the data currently in the data base. If the independent variables associated with the target point are close to the data base averages, then the user can expect a more reliable result to be produced. The coefficient of determination of the polynomial fit through the 10 interpolation points can be presented to the user to assess the scatter in the data. Finally, as shown schematically in Fig. 4, the 10 interpolation points, the polynomial curve, and the prediction can be graphically illustrated on the computer screen to show how the dependent variable behaves as a function of distance along the prediction vector and also indicate the location of the target point along the prediction vector relative to the min and max points. If the dependent variable oscillates wildly, then unreliable predictions can be expected, particularly in the case of extrapolation. In most cases, target points located approximately half way between the min and max points produce the best results.

Testing the New Interpolation/Extrapolation Technique

The proposed method was tested by making predictions based on a data base created using a known function, so that the reliability of the prediction could be assessed. The form of the function used was

$$D_i = \prod_{j=1}^{5}(rn\# + rn\#*x_{j,i} + rn\#*x_{j,i}^2) \tag{3}$$

A set of 15 random numbers, $rn\#$, was required—three for each of the five independent variables used to generate a data set. The random numbers were held constant during the data set creation, so that a consistent set of dependent variables were generated. The intent here was to develop an unbiased, sophisticated, and consistent set of data to provide an objective test of the interpolation/extrapolation technique.

The values of the independent variables used were obtained from a hypervelocity impact data set (Table 1). The nature of this data will be discussed in more detail in the next section. This data set was selected for two reasons. First, it seemed desirable to use a set of actual engineering data to provide a realistic test of the technique. Second, the technique proposed herein did a poor job of predicting the behavior of some of the

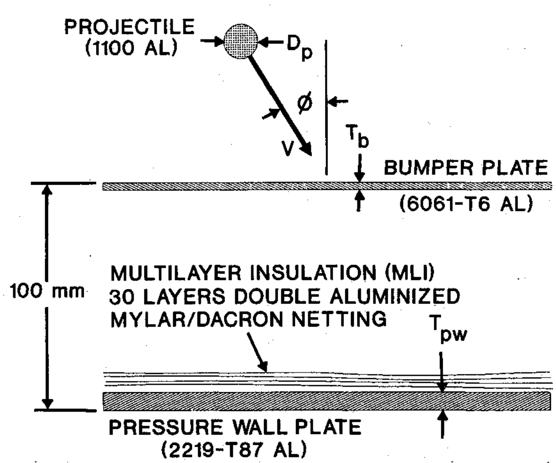

Fig. 6 Schematic drawing of impact specimen.

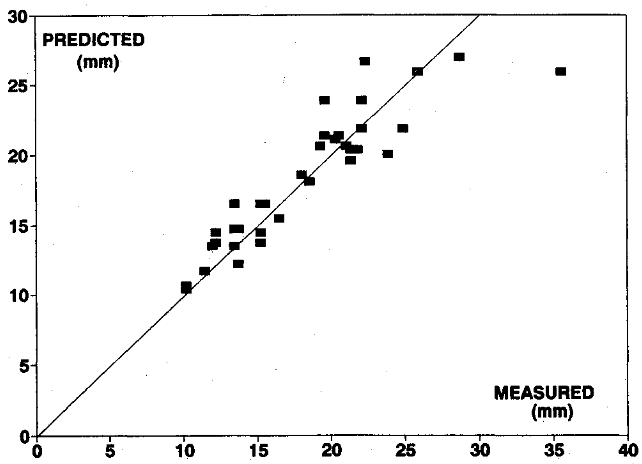

Fig. 7 Plot of measured vs predicted data for the major axis of the bumper plate hole.

Table 1 Experimental data from hypervelocity impact tests

Test ID	Bumper thick. T_b, mm	Pr. wall thick. T_{pw}, mm	Proj. diam. D_p, mm	Impact angle ϕ, deg	Proj. vel. V, km/s	Bump. maj. ax., mm	Bump. min. ax., mm	MLI pen., cm^2	MLI per/chr, cm^2	Pr. wall maj. ax., mm	Pr. wall min. ax., mm
227A	0.81	1.60	6.35	45.00	5.52	15.24	11.68	32.26	51.61	13.46	9.65
227B	0.81	1.60	6.35	45.00	7.12	15.24	10.92	64.65	425.81	25.40	12.70
333	1.02	3.18	4.75	45.00	2.88	10.16	7.62	12.90	32.26	0.00	0.00
334	1.02	3.18	4.75	45.00	3.61	10.16	7.87	8.39	63.23	0.00	0.00
221C	1.02	3.18	4.75	45.00	4.57	11.43	9.14	19.35	51.61	0.00	0.00
221B	1.02	3.18	4.75	45.00	5.89	13.72	10.67	12.90	141.94	0.00	0.00
221A	1.02	3.18	4.75	45.00	6.36	12.19	10.16	12.90	148.39	0.00	0.00
336	1.02	3.18	6.35	45.00	4.47	13.46	10.67	64.52	129.03	14.99	6.35
201B	1.02	3.18	6.35	45.00	5.51	13.46	10.92	64.52	135.48	13.21	11.68
201C	1.02	3.18	6.35	45.00	7.21	13.46	6.35	16.13	161.29	2.54	2.54
203B	1.02	3.18	7.62	65.00	3.67	22.10	11.94	22.58	290.32	0.00	0.00
203A	1.02	3.18	7.62	65.00	6.45	23.88	13.46	29.03	232.26	0.00	0.00
003A	1.02	3.18	7.95	45.00	6.51	19.30	13.72	32.26	129.03	76.20	38.10
338	1.02	3.18	7.95	45.00	6.98	21.34	14.48	83.87	58.06	25.40	17.78
337	1.02	3.18	7.95	45.00	7.00	19.56	13.21	64.52	90.32	27.94	12.70
203F	1.02	3.18	8.89	65.00	3.04	24.89	12.45	13.55	270.97	0.00	0.00
339	1.02	3.18	9.53	45.00	6.49	21.08	17.53	129.03	258.06	50.80	38.10
218B	1.02	4.78	8.89	45.00	6.40	20.32	15.24	483.87	483.87	18.29	15.49
218C	1.02	4.78	8.89	45.00	6.76	21.34	14.99	70.97	270.97	30.73	10.16
230B	1.60	3.18	4.75	45.00	3.23	11.94	9.14	3.87	6.45	0.00	0.00
230A	1.60	3.18	4.75	45.00	4.41	12.19	9.91	6.45	48.39	0.00	0.00
301	1.60	3.18	6.35	45.00	2.95	13.72	10.92	4.26	118.32	0.00	0.00
205A	1.60	3.18	6.35	45.00	4.11	15.49	12.19	11.61	116.13	5.08	5.08
205B	1.60	3.18	6.35	45.00	4.59	16.51	12.45	24.52	335.48	5.08	5.08
205C	1.60	3.18	6.35	45.00	3.30	15.24	12.70	16.13	83.87	7.62	7.62
209B	1.60	3.18	6.35	65.00	6.40	22.10	13.21	5.16	193.55	0.00	0.00
209D	1.60	3.18	6.35	65.00	7.40	19.56	14.48	19.35	206.45	0.00	0.00
207A	1.60	3.18	7.62	65.00	5.86	22.35	14.99	11.61	329.03	4.06	4.06
207C	1.60	3.18	7.62	65.00	7.08	25.91	16.26	103.23	174.19	0.00	0.00
002B	1.60	3.18	7.95	45.00	6.39	20.57	15.75	129.03	77.42	5.59	5.59
211B	1.60	3.18	8.89	45.00	5.85	21.84	17.27	77.42	122.58	27.94	12.70
210B	1.60	3.18	8.89	65.00	5.70	28.70	16.76	41.94	96.77	3.18	3.18
210D	1.60	3.18	8.89	65.00	6.80	35.56	17.27	45.16	212.90	5.84	5.84
303B	1.60	4.06	7.95	45.00	4.34	18.03	14.48	32.90	362.26	0.00	0.00
303	1.60	4.06	7.95	45.00	4.59	18.54	14.73	17.03	166.84	0.00	0.00

dependent variables of Table 1, as will be discussed in the next section. Accordingly, it was of interest to determine if the nature of the data or the prediction technique was at fault for the poor predictions.

Equation (3) was used with two sets of random numbers to generate two sets of consistent data. An analysis was done with each set of data, as follows. Each record (data point) was temporarily removed from the data base, a prediction was made for the independent variables associated with that record, and then the record was returned to the data base. This was done for all of the 35 records in the data base. Thus, all predictions were made with the actual data point of interest removed from the data base.

A typical set of results is shown in Fig. 5, where actual data values are plotted against their corresponding predictions. The dashed line in the figure is a linear least-squares fit through the data of the form $y = mx + b$, where y is the prediction, x is the actual function value, and m and b are parameters to be fit. The coefficient of determination of this fit was 0.937. Assuming a functional form of $y = x$ produced a coefficient of determination of 0.934. Similarly, the other consistent data set produced coefficients of determination of 0.961 and 0.959, respectively. Ideally, the prediction y should exactly equal the actual value x which would result in a coefficient of determination of unity for the line $y = x$.

These results seem to be quite good, considering that the dependent variables were reasonably complicated functions of 15 random coefficients with five independent variables.

Applying the New Technique to Hypervelocity Impact Data

Personnel from the Structures and Dynamics Lab of Marshall Space Flight Center (MSFC) provided the author with a set of experimentally obtained hypervelocity impact data. MSFC has a light gas gun that can launch 2.5–12.7 mm projectiles at speeds of 2–8 km/s.[8] Work is currently in progress at MSFC to qualify the orbital debris protection system under development by Boeing for Space Station Freedom. A schematic of the protection system is shown in Fig. 6. It is based on the classical sacrificial bumper approach first suggested by Whipple.[9] The purpose of the bumper is to break up or, ideally, vaporize the projectile (space debris or micrometeoroids), so that the pressurized spacecraft behind the bumper is impacted with a series of fine particles rather than a single large particle.

The five independent variables associated with the impact data are illustrated in Fig. 6 and listed in Table 1. The projectiles were initially spherical and constructed of 1100 aluminum. The bumper and the pressure walls were made from 6061-T6 and 2219-T87 aluminum, respectively. If a number of different materials were used for the bumper and the other components in the same data base, then the number of independent degrees of freedom would have had to be increased dramatically. This is because material properties, such as densities and melting points, would also have had to be accounted for. The method proposed herein is ideally suited to systems with large numbers of independent variables.

These impact tests were made with the multilayer insulation (MLI) placed directly against the pressure wall. Currently, the plans are to place the MLI in the vicinity of the back of the bumper, because under certain impact conditions the damage to the pressure wall is dramatically increased when the MLI is placed against the pressure wall. The bumper plate was placed approximately 100 mm in front of the pressure wall plate. For this series of data, the pressure wall was unstressed. Currently, testing is being done on stressed panels for comparison with

Table 2 Coefficients of determination for predictions

Data set	Coefficients of determination (y = prediction, x = measured): Line of form $y = mx + b$	Line of form $y = x$
Bumper major axis	0.815	0.811
Bumper minor axis	0.774	0.773
MLI penetration area	0.322	0.289
MLI perforated/charred area	0.042	−0.445
Pressure wall major axis	0.541	0.538
Pressure wall minor axis	0.575	0.566

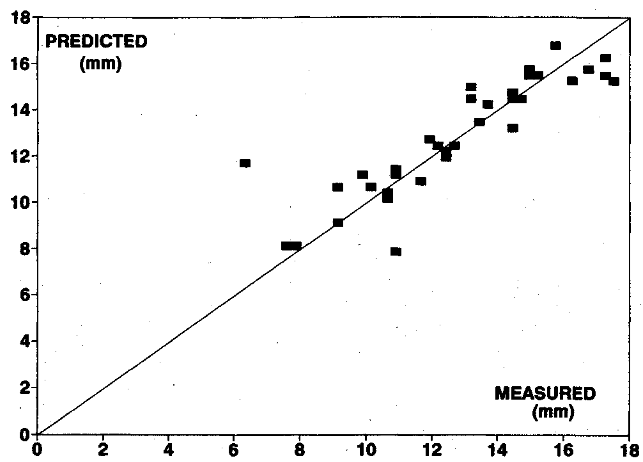

Fig. 8 Plot of measured vs predicted data for the minor axis of the bumper plate hole.

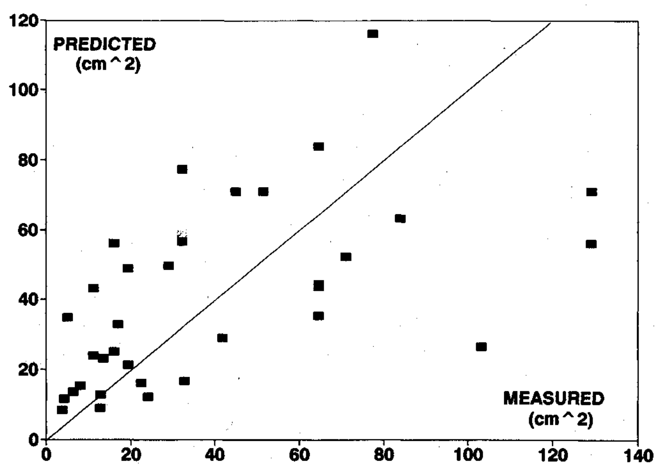

Fig. 9 Plot of measured vs predicted data for the MLI penetration area.

unstressed results. The pressure wall of the station will actually be relatively highly stressed.

As listed in Table 1, the dependent variables measured included the major and minor axis dimensions of the bumper hole, the area of the hole clean through the MLI called the penetration area, the area of the MLI outside of the penetration area obviously damaged by the impact, called the perforated/charred area, and the major and minor axis dimensions of the pressure wall hole. Some comments will now be made on the characteristics of these dependent variables.

The bumper plate hole typically takes the form of a single well-defined, relatively smooth, elliptical hole. The greater the impact angle, the more elliptical the hole. It is not surprising that the bumper plate hole data are the most consistent of all the data, given the relatively simple nature of the damage.

The remainder of the dependent variables are much more affected by characteristics of the fragmentation/vaporization process of the projectile than the bumper hole is. Launch loads typically cause the soft aluminum projectile to deform into a variety of nonspherical shapes. This effect, and the inevitable presence of a random assortment of microscopic flaws in the projectile and bumper, can cause large variations in the nature of the particles (from both the projectile and the bumper) that leave the back face of the bumper after the bumper-projectile impact. Thus, similar testing conditions can produce significantly different damage to the the MLI and the pressure wall.

There is a great deal of inconsistency in the MLI data. In addition to the random processes discussed previously, the inconsistency could be partly due to the difficulty in visually measuring the areas of damage (penetration and perforated/charred) because of the rough, irregular shapes of these areas. Also, a patch of MLI that was just, say, one layer from being totally penetrated would be counted the same as a patch of MLI that had only suffered slight damage to the top of its 30 layers. Work is currently under way to develop more consistent ways of monitoring MLI damage.

It is of interest to predict MLI damage so that local temperature variations in the pressure wall in the vicinity of MLI damage can be estimated. Local cooling could cause condensate to form on the inside surface of the pressure wall. Condensate could cause electrical problems and promote the growth of mold in the station.

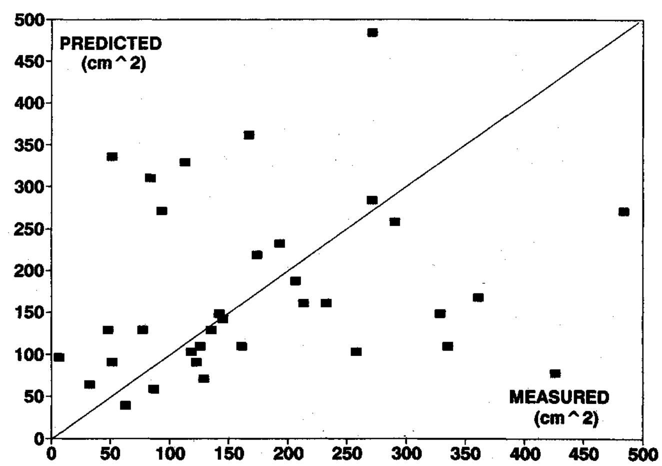

Fig. 10 Plot of measured vs predicted data for the MLI perforated/charred area.

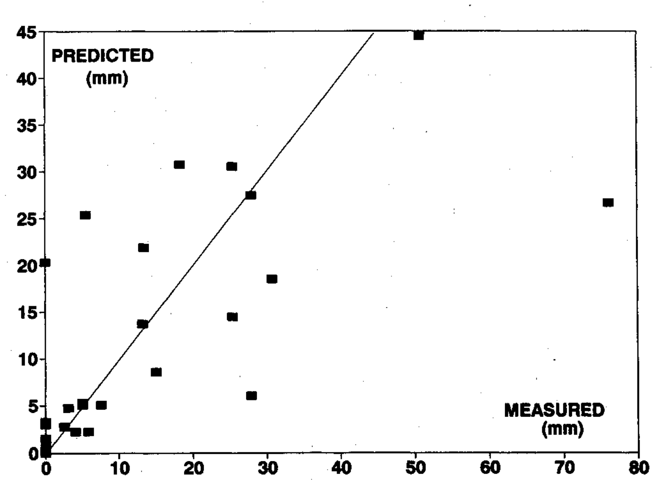

Fig. 11 Plot of measured vs predicted data for the major axis of the pressure wall hole.

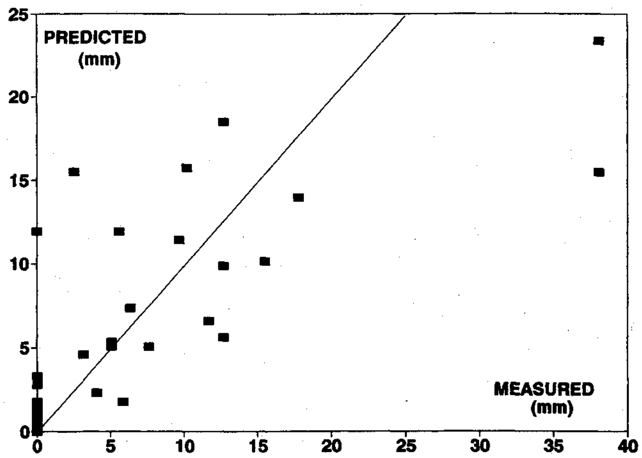

Fig. 12 Plot of measured vs predicted data for the minor axis of the pressure wall hole.

Damage to the pressure wall typically consists of a large number of craters of various sizes, and possibly some penetrations. The craters and penetrations are typically distributed over a relatively large area, as can be seen in the photographs of Ref. 1. The data in Table 1 give the dimensions of the largest penetration in the pressure wall, which would essentially depend on the the largest fragment that results from the bumper-projectile impact. As has been discussed, the same test conditions could produce a large variation in the size of the largest fragment and, hence, the size of the penetration. This leads to scatter in the pressure wall data, but less scatter than that encountered with the MLI data, since the pressure wall damage is easier to measure.

The procedure described previously that was used to test the interpolation/extrapolation technique with the consistent data was also used with the experimental data of Table 1. Each record (data point) was temporarily removed from the data base, a prediction made for the independent variables associated with that data point, and then the data point was returned to the data base. The predicted vs actual data are shown in Figs. 7-12. Also drawn on these figures are solid lines indicating the ideal case of "predicted" = "measured." The coefficients of determination associated with these predictions are given in Table 2. As can be seen from this table, the predictions for the bumper plate are acceptable. The predictions for the pressure wall are marginal, although Figs. 11 and 12 are somewhat pessimistic looking, since a large number of good predictions were made for data located near the origin of the plots (no penetration case). The predictions of MLI damage are poor for penetration area and terrible for perforated/charred area.

Since the proposed interpolation/extrapolation technique produced acceptable results for both the consistent test functions of Eq. (3) and the bumper plate data of Table 1, the poor predictions of MLI and pressure wall damage are probably due to the manner by which damage is currently being assessed. Also, some of the scatter in the data is produced by such effects as the distortion of the projectile during launch and the apparently random assortment of microscopic flaws in the projectile and the bumper. The proposed interpolation/extrapolation technique appears to be a useful tool for engineering design work.

Conclusions and Recommendations

During the course of this study the following conclusions were reached:

1) The proposed interpolation/extrapolation technique is easy to implement, versatile, and reliable for making predictions with consistent data.

2) The current methods of measuring hypervelocity impact damage to the MLI and to the pressure wall produce inconsistent sets of results.

As a result of this study, the following recommendations are offered:

1) The proposed interpolation/extrapolation scheme should be used in cases where conventional techniques fail because a suitable functional form could not be found, where it is anticipated that additional or different independent variables will be required in the future, or where the experimental data base will continue to grow over time.

2) Alternative measures of hypervelocity impact damage to MLI and to the pressure wall plate should be developed.

Acknowledgments

The author wishes to thank Pedro Rodriguez, Sherman Avans, and Jennifer Horn of Marshall Space Flight Center for providing the experimental data and background information, and for enthusiastically supporting this effort. This project was funded by NASA Grant NAG8-123 (10).

References

[1]Schonberg, W. P., and Taylor, R. A., "Penetration and Ricochet Phenomena in Oblique Hypervelocity Impact," *AIAA Journal*, Vol. 27, No. 5, 1989, pp. 639–646.

[2]Coronado, A. R., Gibbins, M. N., Wright, M. A., and Stern, P. H., "Space Station Integrated Wall Design and Penetration Damage Control," Boeing Aerospace Co., Seattle, WA, D180-30550-1, July 1987.

[3]Fraas, A. P., "Protection of Spacecraft from Meteoroids and Orbital Debris," Oak Ridge National Lab., Oak Ridge, TN, ORNL/TM-9904, March 1986.

[4]Gehring, J. W., "Theory of Impact on Thin Targets and Shields and Correlation with Experiment," *High-Velocity Impact Phenomena*, edited by R. Kinslow, 1st ed., Academic, New York, 1970, pp. 117–147.

[5]Maiden, C. J., Gehring, J. W., and McMillan, A. R., "Investigation of Fundamental Mechanism of Damage to Thin Targets by Hypervelocity Projectiles," GM Defense Research Lab., Santa Barbara, CA, GM-DRL-TR-63-225, Sept. 1963.

[6]Bouma, D. D., and Burkitt, W. C., "Multivariable Analysis of the Mechanics of Penetration of High Speed Particles," Martin Marietta Corp., NASA CR-664, Dec. 1966.

[7]Özişik, M. N., *Heat Transfer: A Basic Approach*, 1st ed., McGraw-Hill, New York, 1985, pp. 593–683.

[8]Taylor, R. A., "A Space Debris Simulation Facility for Spacecraft Materials Evaluation," *SAMPE Quarterly*, Vol. 18, Feb. 1987, pp. 28–34.

[9]Whipple, F. L., "Meteorites and Space Travel," *Astronomical Journal*, No. 1161, 1947, p. 131.

Alfred L. Vampola
Associate Editor