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Prediction of Sample Curing Index Data Based on Cubic Hermite Interpolation

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Abstract

Cubic Hermite interpolation is a fundamental and widely-used interpolation algorithm in numerical computation. This method can generate functional expressions based on discrete sampling data to realize data inference and trend prediction. Distinct from other interpolation methods, Hermite interpolation matches not only the function values at interpolation nodes but also the first derivatives at these nodes. This characteristic enables the algorithm to fit the original function more accurately, yielding smoother and more precise curves especially in the vicinity of discrete nodes. In this paper, cubic Hermite interpolation is adopted to predict the performance evolution of civil engineering materials during curing. The test sample contains eleven performance indicators measured at weekly intervals, and the material properties of intermediate weeks are calculated via interpolation. Experimental results verify that cubic Hermite interpolation is applicable to the research problem in this paper and can effectively predict unknown sample indicators from limited measured data.

Keywords

Cubic Hermite Interpolation; Loop Calculation; Interpolation Remainder.

1. Introduction

Cubic Hermite interpolation serves as a basic and common interpolation technique within the system of numerical computing. It constructs functional relations from scattered discrete data to infer and predict unknown values. Its core advantage lies in simultaneously matching function values and first-order derivatives at all interpolation nodes, which delivers better approximation of the real function and smoother fitting curves around sampling points [1].

Cubic Hermite interpolation is mainly applied in two core scenarios:

Function approximation: Construct polynomial expressions from known data points to minimize the deviation between fitting values and the original function.

Curve fitting: Generate continuous fitting curves based on discrete measurements to restore the variation trend of real physical quantities.

Yang et al. (2021) applied cubic Hermite interpolation to forecast the staffing demand of educational institutions, providing reliable data support for steady industry development and educational reform promotion [2]. Liang et al. (2024) proposed an optimized cubic Hermite interpolation algorithm for high-speed rail pier settlement monitoring, whose accuracy was validated to support long-term deformation prediction [3]. This interpolation method can also identify four typical photovoltaic array faults including short-circuit, open-circuit, abnormal aging and partial shading. Luo Xiaomeng adopted Hermite interpolation to reconstruct fingerprint maps and eliminate abrupt value jumps at boundary nodes [4].

The above research proves that Hermite interpolation has extensive engineering application value. This paper employs the algorithm to analyze the time-varying characteristics of eleven

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material performance indicators and reduce the frequency of repeated physical testing and measurement.

2. Theoretical Foundation

For a given function $f(x)$, we sometimes obtain not only its function values at several discrete nodes, but also the corresponding first derivatives at these points. If the interpolating function $P(x)$ satisfies the condition that both its function values and first derivatives are equal to those of $f(x)$ at all these nodes simultaneously, this problem is known as the Hermite interpolation problem, or interpolation with derivative constraints.

Suppose that the function $f(x)$ has known function values and first derivatives at $n+1$ distinct nodes x_i $(i=0,1,\ldots,n)$ over the interpolation interval $[p,q]$. If a function $G(x)$ meets the following conditions:

1) $G(x)$ The polynomial defined on each subinterval is of degree 3;

2) $G(x) \in C^1[a,b]$;

3) $G(x_i)=f(x_i)$, $G'(x_i)=f'(x_i)$, $i=(0,1,\ldots,n)$ [5]

Then $G(x)$ is referred to as the piecewise cubic Hermite interpolation polynomial of $f(x)$ at the $n+1$ nodes x_i.

Therefore,

$$G(x)=h_k y_k(x)+h_{k+1}y_{k+1}(x)+H_k(x)y'_k+H_{k+1}(x)y'_{k+1}$$
$$=(1+2\frac{x-x_k}{x_{k+1}-x_k})(\frac{x-x_{k+1}}{x_k-x_{k+1}})^2 y_k+(1+2\frac{x-x_{k+1}}{x_k-x_{k+1}})(\frac{x-x_k}{x_{k+1}-x_k})^2 y_{k+1}$$
$$+(x-x_k)(\frac{x-x_{k+1}}{x_k-x_{k+1}})^2 y'_k+(x-x_{k+1})(\frac{x-x_k}{x_{k+1}-x_k})^2 y'_{k+1}$$

3. Empirical Analysis

3.1. Problem Statement

Table 1. List of Measured Index Data

Serial No.	Week 1	Week 3	Week 5	Week 7	Week 9	Week 11	Week 13	Week 15
Index 2 (Strength)	1913	1945	1920	2205	2260	2302	2385	2420
Index 3 (Impermeability)	5.12	3.20	6.72	3.36	2.40	4.14	6.43	4.60
Index 4 (Crack Resistance)	21.90	20.00	26.80	27.73	23.40	22.75	25.36	26.03
Index 5 (Freeze-Thaw Resistance)	24.80	25.70	26.80	28.00	30.40	30.00	27.60	30.80
Index 6 (Fluidity)	9.31	9.14	9.14	9.29	9.22	9.33	9.16	9.26
Index 7 (Ductility)	1.80	2.30	1.90	2.10	2.10	1.10	1.50	1.50
Index 8 (Transparency)	28.00	24.00	26.00	22.00	22.00	20.00	19.00	23.00
Index 9 (Carbonation Resistance)	425.11	457.99	492.48	492.08	501.93	598.48	604.44	623.89
Index 10 (Setting Time)	628.10	639.20	648.87	640.33	616.43	614.72	507.14	580.00
Index 11 (Cohesion)	28.00	24.00	26.00	22.00	22.00	20.00	19.00	23.00
Index 12 (Water Retention)	30.58	36.19	49.75	60.58	56.58	60.06	67.99	67.74

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Table 1 records the measured performance indicators of a construction material at different curing weeks. Each row corresponds to one of the eleven physical property attributes of the test specimen.

Cubic Hermite interpolation is implemented on the above dataset to calculate the eleven indicator values for even intermediate weeks.

3.2. Simulation Results and Analysis

The curing week is treated as the independent variable. The raw data table is imported as the file "z.txt", and cubic Hermite interpolation calculation is completed on the MATLAB platform. The predicted interpolation results are shown in Table 2.

Table 2. List of Predicted Interpolation Results

Week 1.00	Week 2.00	Week 3.00	Week 4.00	Week 5.00	Week 6.00	Week 7.00	Week 8.00
1913.00	1936.56	1945.00	1932.50	1920.00	2050.97	2205.00	2238.07
5.12	3.58	3.20	4.96	6.72	5.23	3.36	2.69
21.90	20.24	20.00	23.20	26.80	27.47	27.73	25.71
24.80	25.23	25.70	26.23	26.80	27.34	28.00	29.40
9.31	9.19	9.14	9.14	9.14	9.22	9.29	9.26
1.80	2.17	2.30	2.10	1.90	2.00	2.10	2.10
28.00	25.13	24.00	25.00	26.00	24.00	22.00	22.00
425.11	441.35	457.99	479.44	492.48	492.28	492.08	494.77
628.10	633.83	639.20	645.33	648.87	646.17	640.33	627.21
28.00	25.13	24.00	25.00	26.00	24.00	22.00	22.00
30.58	32.60	36.19	42.46	49.75	56.67	60.58	58.58

Table 2. (Continued) List of Predicted Interpolation Results

Week 9.00	Week 10.00	Week 11.00	Week 12.00	Week 13.00	Week 14.00	Week 15.00
2260.00	2279.98	2302.00	2344.32	2385.00	2407.28	2420.00
2.40	3.02	4.14	5.53	6.43	6.00	4.60
23.40	22.93	22.75	23.92	25.36	25.83	26.03
30.40	30.29	30.00	28.71	27.60	28.45	30.80
9.22	9.28	9.33	9.25	9.16	9.18	9.26
2.10	1.60	1.10	1.30	1.50	1.50	1.50
22.00	21.17	20.00	19.33	19.00	20.19	23.00
501.93	551.04	598.48	601.72	604.44	612.03	623.89
616.43	615.60	614.72	560.51	507.14	523.19	580.00
22.00	21.17	20.00	19.33	19.00	20.19	23.00
56.58	57.72	60.06	64.63	67.99	67.96	67.74

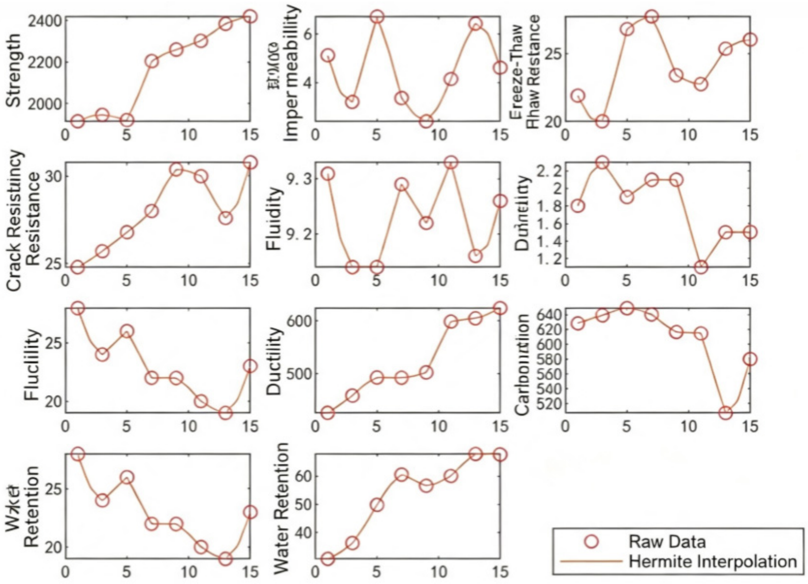

Figure 1. Distribution of Eleven Predicted Performance Indicator Results

Figure 1 Distribution Curves of Eleven Predicted Performance Indicators (Scatter points: raw measured data; Solid lines: cubic Hermite interpolation fitting curves)

The distribution graph clearly reflects the complete intermediate-week indicator values calculated by cubic Hermite interpolation, which fills the blank of untested time points between weekly measurement nodes.

4. Conclusion

In terms of fitting consistency between interpolation polynomials and original functions, Hermite interpolation outperforms conventional polynomial interpolation. By constraining both function values and first derivatives at discrete nodes, the algorithm achieves superior fitting precision and curve smoothness. Nevertheless, Hermite interpolation has strict application prerequisites: it requires complete acquisition of both function values and derivative values at all interpolation nodes, which is difficult to satisfy in most practical engineering tests. In most measurement scenarios, only discrete function values can be collected without derivative information.

Therefore, although Hermite interpolation possesses theoretical advantages in fitting quality, ordinary polynomial interpolation methods are more widely adopted in actual engineering research due to simpler operation and lower data acquisition cost. When derivative data is unavailable, alternative interpolation algorithms including Lagrange interpolation and spline interpolation can be selected to maintain stable prediction accuracy with limited raw measurement data.

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