Postprint: Vibration Load Identification Methods for Pipelines Based on Limited Measurement Point Information

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Date: 2025-11-01T00:00:00+00:00

Abstract

A method for vibration load parameter identification in pipeline systems based on limited measurement information was proposed and validated. Finite element modeling of the forward vibration problem for typical engine pipelines was conducted, and the validity of the established finite element model was experimentally verified. Based on the singular value decomposition algorithm, genetic algorithm, and tabu search algorithm, a method for reconstructing and identifying unknown vibration load information in pipeline systems was proposed and validated, achieving load reconstruction based on both simulated signals and vibration measurement signals. The results indicate that load reconstruction based on the least squares method and singular value decomposition algorithm offers fast computational speed but is susceptible to signal noise, whereas genetic algorithm and tabu search algorithm demonstrate better robustness, enabling effective reconstruction of vibration loads for both simulated and measured vibration signals.

Full Text

Preamble

Vol. 42 No. 5
Oct. 2025

Chinese Journal of Applied Mechanics DOI: 10.11776/j.issn.1000-4939.2025.05.007

Identification Method of Pipeline Vibration Loads with Limited Measurement Information

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Abstract: This paper proposes and validates methods for identifying vibration load parameters in pipeline systems using limited measurement information. Finite element modeling was conducted for the forward vibration problem of typical engine pipelines, and the effectiveness of the established finite element model was experimentally verified. Based on singular value decomposition, genetic algorithm, and tabu search algorithm, methods for reconstructing and identifying unknown vibration load information of pipeline systems were proposed and validated, achieving load reconstruction using both simulated and measured vibration signals. The results demonstrate that load reconstruction based on least squares and singular value decomposition algorithms is computationally fast but susceptible to signal noise, whereas genetic algorithm and tabu search algorithm exhibit better robustness and can effectively reconstruct vibration loads for both simulated and measured signals.

Keywords: singular value decomposition; genetic algorithm; tabu search; load identification; pipeline vibration

Introduction

Pipeline systems, often referred to as the "blood vessels" of liquid rocket engines, are critical components ensuring reliable engine operation. The spatial structure and vibration loads of engine pipeline systems are complex, and these systems operate under harsh conditions including high pressure, large temperature differentials, and high overload. Consequently, vibration-induced failures represent a significant concern. Excessive vibration may cause clamps or pipe joints to loosen, potentially leading to pipe wall cracks, fluid leakage, and catastrophic accidents that severely threaten the operational safety of the engine and rocket. During engine operation and testing, due to narrow space, complex pipeline structure, and sensor mass effects, only limited measurement points can be installed to measure pipeline vibration information, making it impossible to directly obtain the global vibration state of the pipeline.

To prevent serious accidents caused by engine pipeline system vibration, early analysis of vibration sources, global vibration prediction and health assessment of pipeline systems, and implementation of corresponding vibration reduction and safety measures based on evaluation results are essential means to improve engine integrity. Previous research has analyzed vibration sources in engine pipelines, identified parameters affecting vibration response, and proposed structural and layout improvements. However, such methods are typically specific to particular models and lack generality. Traditional load identification methods often require constructing transfer matrices, which compromises reconstruction accuracy. Research has also focused on improving noise resistance, yet inverse problem methods for load identification remain limited.

Reference [21] proposed combining limited measurement information with inverse methods to reconstruct unknown vibration structure and load parameters for global vibration and strength assessment through refined finite element modeling. When both constraint and load parameters are unknown, simultaneous reconstruction faces challenges: different parameter properties hinder effective simultaneous correction, and the large number of unknowns increases ill-posedness, affecting convergence accuracy and efficiency. Addressing this, References [22-23] proposed a stepwise inversion method based on actual engine production and testing conditions, where constraints are first reconstructed using cold-state signals, followed by load reconstruction using actual vibration measurement signals with known constraints, thereby improving accuracy and efficiency. However, this method employs conjugate gradient algorithms for reconstruction, whose results are sensitive to initial value selection and signal-to-noise ratio. Therefore, investigating alternative inversion methods for load identification is necessary.

Considering that engine pipeline systems primarily connect between high-speed rotating pumps, their vibration typically contains several frequency components, manifesting as fixed-end harmonic vibration and random vibration. Based on linear superposition principle, vibration responses can be decomposed by frequency, and load reconstruction can be achieved by reconstructing excitations at each frequency. Due to laboratory limitations, this study validates the proposed methods using concentrated force excitation problems.

This research proposes and validates methods for identifying pipeline system vibration loads based on typical inverse optimization algorithms and limited vibration measurement information. By transforming the load reconstruction problem into an optimization problem minimizing the residual between measured and calculated vibration features, unknown load parameters are reconstructed using deterministic and stochastic algorithms, with comparative analysis of different inversion methods.

1 Pipeline Vibration Identification Method

1.1 Load Parameter Identification Method Based on Limited Measurement Information

The inverse reconstruction problem for unknown loads in pipeline systems can be formulated as an optimization problem. Selecting the residual function between calculated vibration signals under certain load conditions and measured signal characteristic parameters from the actual structure as the objective function (Equation (1)), the load inversion problem becomes an optimization problem of finding the optimal solution within the feasible domain of load parameters that minimizes the objective function.

$$\varepsilon(c) = \sum_{m=1}^{M} \left(X_m(c) - X_m^{\text{obs}}\right)^2$$

where c is the vector of unknown vibration system load parameters; X_m^{obs} is the characteristic parameter of measured vibration signals, which can be displacement, acceleration, or strain signals and generally must include vibration responses in the direction of the loads to be identified; $X_m(c)$ is the characteristic parameter of vibration signals at measurement points calculated using finite element numerical simulation for load parameters c; and M is the number of measurement points. Considering that constraint conditions can be considered unchanged during testing or operation, this study focuses on the inverse reconstruction of vibration load parameters using limited measurement point vibration signals.

Figure 1 [Figure 1: see original paper] shows a typical engine pipeline system where vibration excitation primarily consists of base displacement or acceleration excitation at both ends. For simplified modeling, considering the structural characteristics of the central pipe clamp, its torsional stiffness and axial translation stiffness can be neglected, characterized by two radial stiffness values, while rotational degrees of freedom are constrained at the ends and base excitation is applied to translational degrees of freedom.

The components of the load characteristic parameter vector c are selected as the signal characteristic quantities in three directions at both pipe ends. For harmonic excitation signals, load characteristics can be selected as excitation displacement amplitudes, with excitation frequencies obtained directly from signal analysis. For actual engine random vibration excitation, reconstruction of the power spectral density (PSD) curve amplitude and frequency distribution is required. Due to the complexity of PSD curve distribution, direct reconstruction leads to excessive ill-posedness. However, considering the linear superposition property of steady-state pipeline vibration problems, the PSD curve can be reconstructed in different narrow frequency bands separately and then integrated to obtain total excitation PSD information. Therefore, for random excitation loads, load characteristic parameters in vector c can be selected as narrowband PSD values (given frequency and bandwidth), allowing characterization of loads with six unknown parameters.

The vibration measurement signal X_m^{obs} must be characterized using the same characteristic parameters as the loads to be identified, i.e., amplitude for harmonic vibration and PSD values at specific frequencies and bandwidths for random vibration. Generally, displacement vibration signals contain more structural vibration information and yield better reconstruction results, with measurement point placement requiring rational selection based on pipeline structure and mode shape characteristics.

1.2 Vibration System Load Inversion Identification Algorithms

1.2.1 Load Identification Method Based on Singular Value Decomposition For linear vibration systems, the total response can be obtained through linear superposition of responses from individual excitations:

$$x_j = \sum_{i=1}^{n} x_{ij}^0 P_i$$

where x_j represents the response at measurement point j; x_{ij}^0 represents the response at measurement point j when unit excitation is applied at excitation position i; and P_i represents the excitation applied at position i (where $i = 1, 2, \dots, n$; $j = 1, 2, \dots, m$). This can be written in matrix form as:

$$\mathbf{x}_{m\times 1} = \mathbf{S}_{m\times n}\mathbf{P}_{n\times 1}$$

where $\mathbf{x}$ is the response information at measurement points; $\mathbf{P}$ is the excitation information; and $\mathbf{S}$ is the flexibility matrix of the vibration system. To ensure a unique solution exists, $m \geq n$, meaning the number of measurement points must be greater than or equal to the number of excitations.

Since $\mathbf{S}$ is not a square matrix and cannot be directly inverted, singular value decomposition is introduced to decompose it as $\mathbf{S} = \mathbf{U} \cdot \mathbf{D} \cdot \mathbf{V}^T$, where $\mathbf{U}$ and $\mathbf{V}$ are m- and n-order orthogonal matrices, respectively, and $\mathbf{D}$ is an $m \times n$ diagonal matrix. The unknown system excitation information can then be solved as:

$$\mathbf{P} = \mathbf{V}\mathbf{D}^{-1}\mathbf{U}^T\mathbf{x}$$

1.2.2 Load Identification Method Based on Genetic Algorithm Genetic algorithm (GA) is a heuristic random optimization algorithm with strong robustness, good generality, and no requirement for objective function continuity, facilitating large solution space searches. GA begins with a population representing potential solutions, consisting of multiple individuals. After initial population generation, evolution proceeds according to survival-of-the-fittest principles, producing increasingly better approximate solutions across generations. In each generation, individuals are selected based on fitness in the problem domain, and genetic operators (selection, crossover, and mutation) produce new populations. This process causes populations to evolve like natural evolution, with later generations becoming better adapted to the environment. The optimal individual in the final population can serve as an approximate optimal solution (Figure 2 [Figure 2: see original paper]).

To solve the inverse problem of minimizing the residual function in Equation (1), the load parameter vector is selected as the search space for the genetic population. Following the process shown in Figure 2, optimal load parameters can be obtained from measured vibration signals. The specific calculation steps are:

1) Based on engineering experience and preliminary forward problem calculations, select the range for each load characteristic quantity (i.e., solution bounds). For harmonic vibration, concentrated load amplitude can range from -10 to 10 kN; for random vibration, PSD values can range from 0 to 10,000 g^2/Hz.

2) Population initialization. Set generation counter $n = 0$ and maximum generations N. Use real-number encoding to randomly generate m possible load vectors (individuals) in the selected parameter space as the initial population set $P(0)$.

3) Individual evaluation. Use the reciprocal of the residual between calculated and measured vibration response values from Equation (1) as individual fitness. For each individual' s load parameter vector, calculate the displacement or strain response of the vibration system using the finite element model and commercial software, then compute the residual using Equation (1). Individuals with smaller residuals are closer to the optimal solution, with the individual having the smallest residual defined as the current optimal individual.

4) Termination condition check. If iteration count reaches the preset maximum ($n = N$), output the individual with the current minimum residual as the optimal solution and terminate calculation. Alternatively, if the residual of the current optimal individual falls below a given threshold, terminate and output the converged result. If neither condition is met, proceed to subsequent steps.

5) Selection operation. Apply the selection operator to the population using tournament selection, randomly selecting several individuals (typically 2 or 3) each time and choosing one based on the minimum residual principle until the population is filled as the basis for generating new individuals.

6) Crossover operation. To maintain population diversity, apply the crossover operator to generate new individuals using a blended crossover algorithm. For each pair of selected superior individuals, generate m new individuals (load vectors), where each new individual' s value equals α times the paternal value plus $(1 - \alpha)$ times the maternal value, with $0 < \alpha < 1$ (crossover factor, typically 0.6-0.7).

7) Mutation operation. Apply the mutation operator to the population by replacing newly generated load individuals with completely random load vectors from the solution space according to a given mutation probability. While typically small, mutation probability ensures population diversity and prevents premature convergence to local optima.

8) Based on population set $P(n)$, obtain the next generation population set $P(n + 1)$ using the above selection, crossover, and mutation operations.

9) Return to step 3) to calculate vibration response parameters and residuals for new population individuals until convergence.

1.2.3 Load Identification Method Based on Tabu Search Algorithm Tabu search (TS) is a metaheuristic random search algorithm and an improvement of local search algorithms. It starts from an initial feasible solution, selects a series of search directions for "exploration," and chooses the optimal neighborhood solution as each iteration value. A tabu list marks searched regions to avoid repeated search and local optima. Tabu length represents the number of steps a solution remains tabu—too short may cause local optima, too long increases computation time. Aspiration criteria ensure optimal solutions are not missed due to tabu restrictions.

For the objective function in Equation (1), load parameters are identified through the following steps:

1) Determine load parameter search ranges and TS algorithm parameters, including tabu length L, number of candidate solutions M, maximum iterations N, or termination tolerance, and initialize an empty tabu table.

2) Select a feasible initial load vector based on engineering experience or randomly generate m possible load vectors (individuals) in the search space as the initial solution set $P(0)$.

3) Calculate system responses for the initial solution set and compute residuals using Equation (1).

4) If maximum iterations N are reached or residuals fall within tolerance, stop calculation and output the current optimal solution. If termination criteria are not met, proceed with the following operations.

5) Generate M neighborhood solutions for the current solution and select the candidate solution with the smallest residual as the new solution.

6) Check if the new solution satisfies aspiration criteria: if its residual is smaller than any previous solution, it can be aspired; if all possible solutions are tabu, aspire the solution with the smallest residual; if satisfied, use the new solution as the current optimal solution and update the tabu table. Otherwise, select the non-tabu candidate solution with the smallest residual as the current solution and update the tabu table.

7) Return to step 3) to calculate vibration response parameters and residuals for the new solution until convergence.

2 Load Identification for Typical Engine Pipelines Using Simulated and Measured Signals

Based on the forward vibration problem model and inversion algorithms presented in this study, a typical engine pipeline structure vibration load identification program was developed using ANSYS APDL language. To validate the method and program effectiveness, load reconstruction was performed using both numerically simulated vibration signals and laboratory-measured vibration signals. To consider vibration noise effects, 5% white noise was added to calculated signals. The reconstruction results based on simulated and measured signals are presented below.

2.1 Forward Vibration Problem Model for Typical Engine Pipelines

For the typical engine pipeline structure shown in Figure 1, forward vibration problem modeling and calculation were first performed. The pipeline consists of straight and bent sections, including a central clamp and flanges fixed to the engine body, with an end-to-end distance of approximately 1.43 m and total spatial length of about 1.86 m. Using ANSYS APDL, the straight and bent sections were modeled using PIPE289 straight pipe elements and EBLOW290 bend elements, respectively, with fully rigid connections between sections. Element mesh size was 0.5 mm, resulting in 7,319 nodes and 3,659 elements. The pipe clamp was equivalently modeled as two radial line spring elements with identical stiffness. For concentrated excitation, sinusoidal excitations at the same frequency were applied in X, Y, and Z directions at the pipeline center; for base excitation, prescribed displacement excitations were set in three translational directions at pipe ends; for random vibration, narrowband power spectral density (PSD) excitation with given center frequency and bandwidth was applied. Pipeline material properties: elastic modulus 196.5 GPa, Poisson' s ratio 0.3, density 7,890 kg/m^3.

Figure 3 [Figure 3: see original paper] shows the vibration measurement system for a typical pipeline system. To validate the finite element model, a vibration experimental system was built for a single-end fixed pipeline to measure and calculate natural frequencies. Through hammer impact testing and spectral analysis of free decay response signals, the first three natural frequencies were measured as 7.08 Hz, 31.10 Hz, and 111.27 Hz. Based on the finite element model and experimental boundary conditions, the first three natural frequencies of the cantilever pipeline were calculated and compared with experimental results in Table 1 . The errors between experimental and simulated frequencies are less than 5%, demonstrating the validity of the finite element model.

Table 1 Comparison of measured and simulated natural frequencies for single-end fixed pipeline (unit: Hz)

Laboratory vibration experiments were conducted under the conditions shown in Figure 3. The pipeline was fixed at one end with a hoop, and an electromagnetic exciter applied harmonic excitation to the straight section through a connecting rod, with a force sensor measuring actual dynamic loads and displacement sensors measuring displacement amplitudes at various points. The dynamic signal testing and analysis system recorded responses and vibration information. The comparison between experimental and simulation results shows close agreement, further validating the finite element model.

Table 2 Vibration test and simulation results for single-end fixed pipeline

2.2 Parameter Reconstruction Results Based on Numerical Simulation Signals

Load parameter reconstruction for concentrated force harmonic vibration was first performed on the typical pipeline structure shown in Figure 1 using finite element model numerical simulation signals. The pipeline finite element model is identical to that in Section 2.1. Harmonic excitation forces at 60 Hz were applied in X, Y, and Z directions at nodes 1,938 (excitation point 1) and 3,750 (excitation point 2) with amplitude 200 N. Displacement amplitudes in X, Y, and Z directions at nodes 2,518 (measurement point 1) and 4,250 (measurement point 2) were used as vibration signal characteristic parameters, with excitation amplitudes as reconstruction targets (the unknown vibration system load characteristic parameter vector). To analyze noise resistance and robustness, 5% white noise was added to simulated signals. GA parameters: population size 40, crossover probability 0.7, mutation probability 0.05, maximum generations 200. TS parameters: candidate solutions 20, tabu length 5, maximum iterations 200. Load parameter reconstruction results based on the three optimization algorithms are shown in Tables 3 through 5 .

Table 3 Load reconstruction results based on SVD (unit: N)

Table 4 Load reconstruction results based on GA

Table 5 Load reconstruction results based on TS

As shown in Tables 3-5, SVD-based reconstruction results are very close to true values. However, when reconstruction characteristic parameters contain noise, SVD results show large errors. In contrast, GA and TS reconstruction loads are essentially consistent with actual loads, demonstrating algorithm robustness and program effectiveness.

2.3 Parameter Reconstruction Results Based on Actual Measurement Signals

Under laboratory conditions, unknown load parameters of a typical pipeline were reconstructed based on measured signals. As shown in Figure 3, Z-direction harmonic excitation forces at 15 Hz and 20 Hz were applied at 998 mm from the fixed end (excitation point 1). The Z-direction displacement amplitude at 885 mm from the fixed end (measurement point 1) was used for load reconstruction through forward problem calculation, while measured and calculated Z-direction vibration displacements at 846 mm from the fixed end (measurement point 3) were used for validation of reconstructed load results. Due to small displacements, measurement errors are inevitable. Maximum generations for both GA and TS were set to 40; other reconstruction parameters are identical to Section 2.2. Reconstruction results are shown in Tables 6 through 8 .

Table 6 Load reconstruction results for single-end fixed pipeline harmonic vibration based on SVD

Table 7 Load reconstruction results for single-end fixed pipeline harmonic vibration based on GA

Table 8 Load reconstruction results for single-end fixed pipeline harmonic vibration based on TS

After obtaining displacement information and the flexibility matrix, SVD requires only matrix operations, making it extremely fast (less than 0.1 s). However, because SVD load reconstruction depends on the transfer matrix, the solution of the linear equation system is severely affected by observation noise due to matrix condition number issues, potentially yielding reconstructed loads far from true values and demonstrating poor noise resistance. In contrast, GA and TS, as stochastic global search algorithms, can often avoid local optima after extensive computation. Even with noise in signal parameters, reconstruction errors remain within reasonable ranges. However, due to repeated finite element calculations during iteration, computational cost becomes substantial for complex models with dense meshing, often requiring several hours or even tens of hours.

Therefore, SVD-based load reconstruction is only suitable for high-precision measurement conditions, while GA and TS are more universally applicable. Validation through comparison of measured and reconstructed displacements at measurement point 3 confirms these conclusions.

Conclusion

This study established a finite element model for the forward vibration problem of typical engine pipelines and implemented load reconstruction using three inverse optimization algorithms. Load parameter reconstruction was performed using both numerically simulated and experimentally measured vibration signals, validating method accuracy and effectiveness. The results show that load reconstruction based on least squares and singular value decomposition algorithms is computationally fast but susceptible to signal errors, while stochastic algorithms (genetic algorithm and tabu search algorithm) exhibit better robustness and can effectively reconstruct loads for both simulated and measured vibration signals, albeit requiring greater computational effort. Future work will combine advantages of different algorithms to simultaneously improve accuracy and reduce computational cost.

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(Edited by LI Kunlu)

Note: Figure translations are in progress. See original paper for figures.