# Optimal Parameter Prediction in Tuned Liquid Mass Dampers Using Machine Learning Classification Models

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## ABSTRACT

**This study proposes an integrated framework that combines dynamic modeling, numerical optimization, and machine learning classification to predict the optimal design parameters of Tuned Liquid Mass Dampers (TLMDs). Two primary outputs—the optimal frequency ratio and optimal damping ratio—were analyzed using six classification models: Logistic Regression, Decision Tree, Random Forest, K Nearest Neighbors (KNN), Support Vector Machine (SVM), and Naive Bayes. Two structural configurations were examined: a single-story and a five-story shear building, each equipped with rooftop TLMDs mounted on elastomeric pads. Dynamic responses were obtained for six earthquake records using time history analysis, with liquid motion modeled by the Housner model. Optimal elastomeric pad parameters for various tank configurations were determined via the Pattern Search algorithm. The results revealed that for the optimal frequency ratio in the single-story structure, KNN and Random Forest achieved the highest F1 score (~0.73), whereas in the five-story building, prediction accuracy declined and Naive Bayes performed best (~0.68). Regarding the optimal damping ratio, Naive Bayes excelled in both structures, particularly in the five-story model. Confusion matrix analysis indicated that most errors occurred in the intermediate class, primarily due to feature overlap. By significantly reducing computational time and eliminating the need for exhaustive numerical simulations, the proposed data-driven methodology supports reliable decision-making in both preliminary and detailed stages of TLMD design. Moreover, the framework is extendable to other passive vibration control devices and more complex structural systems, advancing the concept of intelligent, efficient, and precise design tools in structural engineering.**

## KEYWORDS

**Tuned Liquid Mass Damper, Machine Learning Algorithms, Prediction, Classification, Optimization**

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## 1. Introduction

Vibration mitigation of structures subjected to dynamic loads such as earthquakes and wind is a fundamental concern in structural engineering. Tuned mass dampers (TMDs) are widely used passive control devices; however, their performance is highly sensitive to variations in structural properties and seismic characteristics, which may significantly reduce their effectiveness under uncertain loading conditions [1].

Tuned liquid dampers (TLDs) have been proposed as an efficient alternative to TMDs by exploiting liquid sloshing and wave-breaking mechanisms, offering advantages such as reduced added mass and ease of installation. Previous studies have demonstrated that TLDs are particularly effective for flexible, long-period structures and can noticeably reduce seismic and wind-induced responses of tall buildings [2-4]. Nevertheless, the performance of conventional TLDs strongly depends on accurate frequency tuning, which is governed by tank geometry and liquid depth, limiting their applicability to short-period structures.

To overcome this limitation, deep liquid tanks commonly available as rooftop water reservoirs have been modeled using the Housner approach, in which the liquid mass is decomposed into rigid and sloshing components [5]. This concept has led to the development of tuned liquid mass dampers (TLMDs), which utilize the inherent dynamic behavior of deep liquid tanks without requiring additional tuned masses. However, determining optimal TLMD parameters remains computationally demanding, motivating the use of machine learning–based classification models for fast and reliable prediction of optimal damper properties.

## 2. Methodology

### 2.1 Dynamic and Optimization Modeling

Two shear buildings—a one-story and five-story configuration—were modeled (see Table 1). Rooftop TLMDs were installed on elastomeric pads that govern system stiffness and damping. The liquid behavior followed Housner's model, where the rigid mass and sloshing mass vary as functions of the liquid depth ratio β.

**Table 1. Shear Structure Specifications**

| Structure | Stories | Mass (ton) | Stiffness (KN/m) | Damping (KN.s/m) |
|---|---|---|---|---|
| One-story | 1 | 100 | 15791 | 1/25 |
| Five-story | 1-5 | 100 | 160000 | 800 |

Optimal system parameters were determined to minimize the root-mean-square (RMS) acceleration responses using the Pattern Search algorithm, a derivative-free global optimizer suitable for nonlinear systems.

### 2.2 Data Generation and ML Framework

Time-history analyses under six earthquake records (Bam, Duzce, Hector Mine, Kobe, Northridge, Loma Prieta) produced optimized parameter datasets (900 samples per structure).

Values were divided into three performance classes (Class 0: 0-75%, Class 1: 75-90%, Class 2: 90-100%) to reflect typical and critical operating ranges.

Six supervised learning algorithms—Logistic Regression, Decision Tree, Random Forest, KNN, SVM, and Naive Bayes—were trained with 70/30 train-test splitting and 10-fold cross-validation. Performance was assessed using Precision**,** Recall**,** F1-score, and ROC-AUC. Hyper-parameters were optimized (e.g., KNN = 5, SVM-RBF kernel C=1, $\gamma = 0.1$).

## 3. Results and Discussion

The ML models demonstrated clear differentiation between the prediction tasks for frequency ratio and damping ratio.

For the single-story structure, KNN and Random Forest achieved F1 $\approx 0.73$ for frequency ratio, while Logistic Regression and Naive Bayes obtained the highest ROC-AUC (~0.79).

For the five-story structure, Naive Bayes outperformed others with F1 $\approx 0.68$ and ROC-AUC $\approx 0.72$ for frequency ratio, and F1 $\approx 0.84$ and ROC-AUC $\approx 0.93$ for damping ratio (see Fig 1 and Table 2,3).

It is observed that ROC-AUC values improved for damping ratio prediction, reflecting clearer statistical separability of the data (see Fig 1 and Table 2,3).

These highlight that misclassification mainly occurs in Class 1, where overlapping physical parameters hinder boundary definition among classes.

Overall, ML models captured complex interrelations between structural dynamic responses and TLMD parameters effectively, providing stable generalization on unseen data.

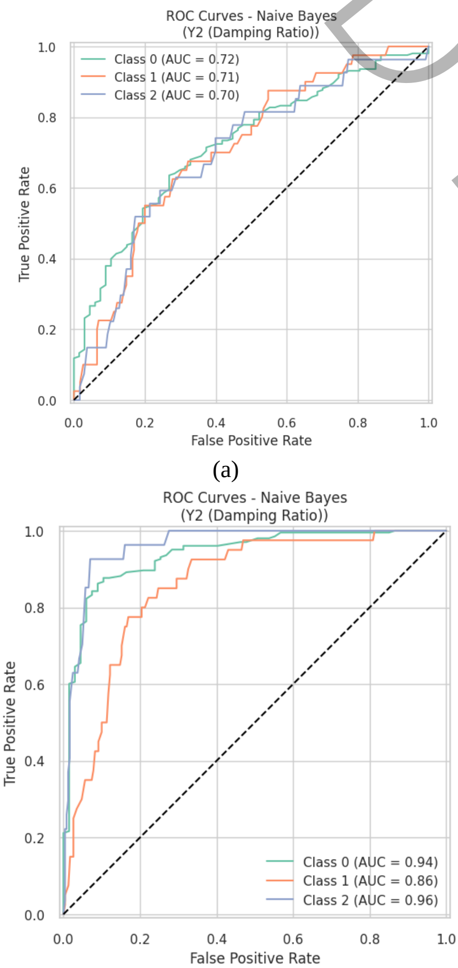
**Table 2. Performance metrics for Frequency Ratio on a one-story structure.**

| Algorithm | F1-Score | Weighted ROC AUC |
|---|---|---|

| | | |
|---|---|---|
| Logistic Regression | 0/68 | 0/795293 |
| K-Nearest Neighbors | 0/73 | 0/699628 |
| Decision Tree | 0/72 | 0/686689 |
| Random Forest | 0/73 | 0/72594 |
| Support Vector Machine | 0/7 | 0/675214 |
| Naive Bayes | 0/69 | 0/791819 |

**Table 3. Performance metrics for Frequency Ratio on a five-story structure.**

| Algorithm | F1-Score | Weighted ROC AUC |
|---|---|---|
| Logistic Regression | 0/55 | 0/705393 |
| K-Nearest Neighbors | 0/63 | 0/528941 |
| Decision Tree | 0/65 | 0/495284 |
| Random Forest | 0/63 | 0/519190 |
| Support Vector Machine | 0/66 | 0/662813 |
| Naive Bayes | 0/68 | 0/721127 |




(b)

**Figure 1. Performance metrics for Frequency Ratio on a (a) one-story structure (b) five-story structure.**

## 4. Conclusion

An integrated data-driven framework was developed to efficiently predict optimal parameters of TLMDs using machine learning classification.

By coupling Housner-based dynamic modeling with statistical learning, the study demonstrated accurate and physically consistent predictions with substantial reduction in computational effort.

Naive Bayes showed the best overall balance between precision, interpretability, and training stability, confirming the feasibility of ML-assisted TLMD design.

The methodology can be readily extended to multi-directional damping systems and tall buildings, promoting intelligent automated structural design practice.

## 5. References

[1] R. Greco, M. Morga, Optimum design of tuned mass dampers under earthquake excitations , The Structural Design of Tall and Special Buildings, 28 (2019) e1672.
[2] P. Banerji, Tuned liquid dampers for controlling earthquake response of structures , Earthquake Engineering & Structural Dynamics, 29 (2000) 587-602.
[3] V.J. Modi, F. Welt, Damping of wind-induced oscillations through liquid sloshing, Journal of Wind Engineering and Industrial Aerodynamics, 30 (1998) 85-94.
[4] Y. Tamura, Effectiveness of tuned liquid dampers under wind excitation, Engineering Structures, 17 (1995) 609-621.
[5] G.W. Housner, The dynamic behavior of water tanks, Bulletin of the Seismological Society of America, 53 (1963) 381-387.