

Physics-Guided Regime-Switching CatBoost for Blast Damage and Instantaneous Building Resilience Assessment

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ABSTRACT

Rapid estimation of building damage immediately after an explosion is essential for prioritizing inspections and supporting emergency decisions. This study develops a physics-guided, regime-switching machine-learning framework to predict building-level blast damage and derive an instantaneous resilience measure from the predicted residual performance. The dataset contains 432 building records described by 11 predictors representing blast intensity, exposure, attack regime, surrounding protection, and architectural and structural characteristics. To reduce optimistic validation caused by repeated or highly similar building profiles, the data were split at the profile-group level, producing a locked internal holdout that remained untouched during feature selection and model development. Hopkins-Cranz scaled distance was introduced as a physics-guided feature, while direct impacts were routed to a specialized CatBoost branch and all other cases to a general branch. Out-of-fold residual correction, constrained affine calibration, SHAP/ALE interpretation, and group-aware conformal prediction were incorporated into the final pipeline. On the locked holdout, the proposed model achieved MAE = 7.13, RMSE = 10.07, and $R^2 = 0.872$. Although XGBoost obtained a slightly lower overall MAE of 7.00, the difference was not statistically significant. In direct-impact cases, the regime-switching model reduced MAE from 11.21 to 8.19, indicating a clearer benefit in the safety-critical regime for which it was designed. Scaled distance, actual standoff distance, surrounding barriers, window-to-wall ratio, and TNT-equivalent mass were consistently influential. A safety-oriented conformal interval achieved 93% empirical coverage. The framework is therefore intended as a rapid screening and decision-support tool rather than a substitute for detailed structural analysis or field inspection.

KEYWORDS

Blast damage, Instantaneous resilience, Physics-guided machine learning, Regime switching; SHAP.

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1. Introduction

Blast loading can damage a building within seconds, from glazing and façade failure to local collapse. The outcome depends not only on explosive mass, but also on standoff distance, geometry, reflection conditions, structural characteristics, and surrounding shielding [1]. Buildings exposed to apparently similar threats may therefore experience very different damage levels.

High-fidelity numerical analyses can reproduce blast-structure interaction in detail, but they are too data- and computation-intensive for rapid screening of many buildings. Machine-learning models offer a faster complement for learning nonlinear relationships in heterogeneous building data [2, 3]. For engineering use, however, accuracy alone is not enough: validation must limit leakage between similar records [4], and predictions should be interpretable [5] and accompanied by uncertainty estimates [6]. Recent building-level work has also shown the value of explainable ML for explosive-effect assessment [7].

This study brings these requirements together in a building-level, physics-guided regime-switching framework. The main idea is simple: keep physically meaningful blast information in the model, treat direct impacts as a distinct regime, and evaluate the predictions with transparent validation, interpretation, and uncertainty analysis. Instantaneous resilience is used here only to describe initial residual performance after the event, not long-term recovery.

2. Methodology

The dataset comprised 432 damaged-building records and 11 predictors covering blast intensity, exposure, attack regime, surrounding protection, and architectural and structural characteristics. Damage was represented on a continuous 0-100% scale. Repeated predictor profiles were grouped before splitting, producing 346 development records and 86 records in a locked internal holdout with no profile overlap.

Physics-guided feature engineering introduced Hopkins-Cranz scaled distance, while the final CatBoost architecture used a general branch and a dedicated branch for direct impacts. Feature selection and model tuning were carried out only on the development data using group-aware cross-validation. XGBoost was retained as the main benchmark.

Model interpretation combined SHAP, ALE, and permutation importance. Prediction uncertainty was quantified using regime-aware conformal intervals. Instantaneous resilience was derived from predicted damage and therefore represents immediate post-event performance rather than recovery over time.

3. Results and Discussion

During development, gradient-boosting models clearly outperformed linear baselines, confirming the nonlinear

structure of the problem. XGBoost achieved the lowest average validation error, while CatBoost showed a smaller training-validation gap. The regime-switching structure added little overall error but improved performance in the direct-impact cases for which it was designed. On the locked holdout of 86 records, the regime-switching CatBoost achieved MAE = 7.13, RMSE = 10.07, and $R^2 = 0.872$. XGBoost reached MAE = 7.00, RMSE = 9.85, and $R^2 = 0.877$. The overall difference was not statistically significant, so the value of the proposed model lies mainly in its behavior within the physically distinct direct-impact regime.

For all direct impacts, the proposed model reduced MAE from 11.21 to 8.19, about a 27% improvement, while preserving nearly the same overall accuracy as XGBoost (Table 1). This is important because the gain appears in a safety-sensitive regime where underestimating damage can directly affect inspection priorities.

The SHAP results support the physical logic of the model. Scaled distance was the dominant predictor in both branches, while standoff distance, surrounding shielding, TNT-equivalent mass, and window-to-wall ratio also contributed strongly. In the specialized branch, the interaction between direct impact and scaled distance became more influential, indicating that the model learned a distinct response pattern rather than simply treating direct impacts as more severe ordinary blasts.

Table 1. Key results on the locked internal holdout.

Indicator	Result
Overall proposed model	MAE=7.13; RMSE=10.07; $R^2=0.872$
Overall XGBoost benchmark	MAE=7.00; RMSE=9.85; $R^2=0.877$
Direct impacts (n = 9)	MAE=8.19 vs. 11.21 (27% lower)
Safety-oriented conformal interval	93% empirical coverage

Figure 1 provides the model-level interpretation. In the general branch, scaled distance Z was the dominant predictor, followed by surrounding shielding, actual standoff distance, window-to-wall ratio, and TNT-equivalent mass. In the specialized branch, the direct-impact interaction with scaled distance became especially influential. This supports the regime-switching premise: direct impacts are not merely more severe versions of ordinary standoff events, but can follow a distinct learned damage regime. The SHAP patterns should nevertheless be interpreted as learned associations rather than causal rankings of structural resistance.

Uncertainty analysis further showed that point predictions should not be used in isolation. The safety-oriented conformal configuration achieved 93% empirical coverage on the holdout, while the widest

intervals were associated with difficult severe-damage cases. The practical implication is that a building with high predicted damage or a wide uncertainty interval should receive more conservative treatment and a higher priority for field inspection. The instantaneous resilience output follows the same logic: it summarizes initial residual performance immediately after the event, but it does not include repair time, recovery resources, or long-term restoration dynamics.

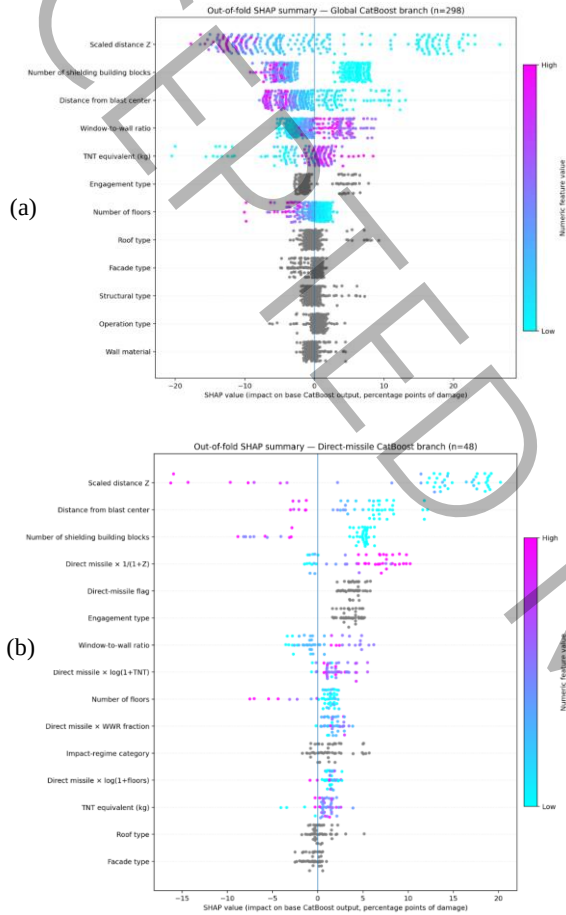


Figure 1. SHAP beeswarm plots for (a) the general CatBoost branch, (b) the direct branch.

Feature-ablation analysis provided additional evidence for the physics-guided design. Adding scaled distance to the 11 raw predictors reduced cross-validated MAE by approximately 2.6–2.8%, whereas replacing the original mass and distance variables entirely with scaled distance degraded performance. Expanding the feature space to 19 engineered variables did not yield a stable gain and introduced substantial redundancy, including 23 feature pairs with Spearman correlation of at least 0.90. The final model therefore retained both the original mass and distance variables and the scaled-distance feature. This result is important because it shows that physics-guided machine learning does not require maximal feature engineering; a compact feature set can preserve physical meaning while limiting unnecessary complexity and overfitting.

A supplementary comparison with classical blast relationships was performed for the 75 holdout records with positive standoff distance, where such relationships

remain within their conventional domain of application. The proposed CatBoost pipeline achieved MAE = 6.77 in this subset, compared with MAE = 9.38 for the best classical alternative based on the Hansen-Newmark relationship with logistic mapping. The classical model therefore showed roughly 28% higher error. This does not invalidate conventional blast equations, which remain essential for describing hazard intensity; rather, it indicates that TNT mass and distance alone do not fully explain whole-building damage when shielding, envelope characteristics, structural system, and attack regime also contribute to the observed response.

4. Conclusion

The study demonstrates that building-level blast damage cannot always be represented adequately by one global relationship across all loading regimes. The proposed physics-guided regime-switching CatBoost framework preserved competitive overall accuracy while improving prediction in direct-impact cases, where the damage mechanism is more severe and safety-sensitive. Its value therefore lies less in a universal reduction of average error and more in explicitly representing regime heterogeneity, controlling leakage, and combining prediction with interpretation and uncertainty. The framework can support rapid screening, estimation of initial residual performance, and prioritization of post-event inspections. Nevertheless, the holdout was internal to the same data source, and the direct-impact subsets were small; independent event- or region-based validation is required before broader operational deployment. The method should be used as a decision-support tool and not as a replacement for detailed structural analysis or field assessment.

5. References

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