**Weekly update**

**May 30, 2024**

Grade the exam 2.

Learning some skills about GitHub website.

**May 29, 2024**

Proctor the exam 3 and grade the assignment 7, 8.

**May 28, 2024**

Read papers:

**Lagaros et al. 2022 “Artificial Intelligence (AI) Applied in Civil Engineering”**

* AI tools can handle big data, perform complex analyses, and improve decision- making process.
* Directions and trends:
  + Optimization methods: Particle Swarm Optimization (PSO), genetic algorithms (GA), and the Gold Rush Optimization (GRO) algorithm
  + Combined Machine Learning and Optimization methods
  + Combined and Multiple AI-Based methods: predicting bearing capacity, dam deformation, and excavation damage zone thickness.
  + Applications of CNN:
    - seismic safety evaluation, bridge vibration measurement, and crack detection.
    - UAVs combined with CNNs for bridge monitoring

**Mogheisis et al 2023 “Probability Assessment of the Seismic Risk of Highway Bridges with Various Structural Systems (Case Study: Tehran City)”**

**Key points:**

1. Classification of bridges

* The bridges were categorized into six types based on structural systems: simple, steel, concrete slab box, concrete slab–steel box, concrete slab, and steel girder–concrete slab.
* The bridges were further classified based on their inclusion of seismic design, particularly distinguishing between those built before and after the implementation of seismic design codes in 2001.

1. Seismic Hazard and Scenario Earthquakes:

* A synthetic earthquake catalog was created using Monte Carlo simulations, encompassing 84,000 potential earthquake scenarios for Tehran.
* For practical risk analysis, 50 representative ground motion records were selected using an optimization-based probabilistic scenarios (OPS) algorithm.

1. Seismic Fragility Curves:

* Fragility curves were developed for four damage states (slight, moderate, extensive, complete) for each bridge type using decision tree analysis and validated with incremental dynamic analysis (IDA).
* These curves help predict the probability of different levels of damage under various seismic intensities.

1. Seismic risk analysis:

* The risk was calculated considering both direct and indirect damages. Direct damages relate to the structural impacts, while indirect damages encompass broader socio-economic consequences like increased traffic and fuel consumption.
* The analysis considered the reconstruction time index and the importance index to quantify indirect damages.

1. Conclusions:

* The study highlights the critical need for seismic risk assessment and appropriate retrofitting of highway bridges to enhance urban resilience.
* The findings suggest that bridges with outdated designs are more vulnerable to seismic events, emphasizing the importance of modern seismic design codes.
* By identifying the most vulnerable bridge types and their risk levels, the research provides valuable insights for policymakers and engineers to prioritize retrofitting and rehabilitation efforts.

**May 27, 2024**

**Jalayer et al 2015 “Bayesian Cloud Analysis: efficient structural fragility assessment using linear regression”**

This paper presents a novel Bayesian approach to Cloud Analysis for structural fragility assessment under seismic events.

**Key points:**

1. Methods comparison: comparing Incremental Dynamic Analysis (IDA) and Multiple-Stripe Analysis (MSA) with the Cloud Method and highlights the efficiency of the cloud analysis.
2. Cloud analysis:

* Regression-Based Probabilistic Model: Utilizes non-linear dynamic analysis results in a log-normal regression model.
* Fragility Calculation

1. Bayesian Framework and Monte Carlo Simulation

**May 26, 2024**

**Mazumder et al\_2021 “Failure risk analysis of pipelines using data-driven machine learning algorithms”**

This paper aims to provide a more efficient ML algorithms for failure risk prediction.

**Key Points:**

1. Data collection: A comprehensive dataset of pipeline characteristics was generated, including geometric properties, corrosion pit dimensions, and material characteristics.
2. Machine Learning Models:

* Eight ML algorithms were evaluated: K-Nearest Neighbors (KNN), Decision Tree (DT), Random Forest (RF), Naïve Bayes (NB), AdaBoost, XGBoost, LightGBM, and CatBoost.
* The models were trained and tested using the generated dataset, and their performance was evaluated based on a confusion matrix and computational efficiency.

1. Results:

* The DNV RP-F101 model provided the lowest variability in failure pressure prediction.
* XGBoost emerged as the optimal algorithm for predicting pipeline failure risk due to its high accuracy and computational efficiency.
* Even the slowest ML algorithm was significantly faster than the physics-based model, with XGBoost being more than 220 times faster.

1. Limitations and Future Work

* The study primarily considered external corrosion and relied on experimental burst test data, which may have constraints.
* Future research should include actual failure data and consider internal corrosion effects for a more comprehensive analysis.

**AI-** **Sabaeei et al. 2023 “Prediction of oil and gas pipeline failures through machine learning approaches: A systematic review”**

**Key Points**

1. ML methods: artificial neural networks (ANNs), support vector machines (SVMs), and hybrid machine learning (HML) algorithms.
2. Applications

* **Artificial Neural Networks (ANNs)**: ANNs have been widely used due to their ability to model complex relationships in data. Studies have applied ANNs for predicting various defects in pipelines using data from magnetic flux leakage sensors, field records, and simulations.
* **Support Vector Machines (SVMs)**: SVMs are effective for high-dimensional data and have been used to develop predictive models for pipeline failures.
* **Hybrid Machine Learning (HML)**: Combining multiple ML techniques can enhance prediction accuracy and reduce prediction time. HML approaches have shown significant improvements over standalone ML models.

**Xiao et al 2024 “Predicting failure pressure of corroded gas pipelines”**

**Key Points**

1. ML algorithms:

* **Artificial Neural Networks (ANN)**: Used for their ability to model complex nonlinear relationships between input features and the target variable.
* **Support Vector Regression (SVR)**: Utilizes support vector machines for regression tasks, effective in handling nonlinear data.
* **K-Nearest Neighbors (KNN)**: A non-parametric method used for regression based on averaging the outcomes of the nearest neighbors.
* **Decision Trees (DT)**: Employed for their simplicity and interpretability in modeling decision rules based on feature splits.
* **Random Forest (RF)**: An ensemble method that combines multiple decision trees to improve prediction accuracy and reduce overfitting.
* **AdaBoost**: A boosting technique that combines weak learners to form a strong predictive model by focusing on misclassified instances.
* **Gradient Boosted Decision Trees (GBDT)**: An ensemble method that builds decision trees sequentially, each one correcting the errors of its predecessor.

1. Model Interpretation: SHAP (SHapley Additive exPlanations) analysis reveals the importance of various features, such as the ratio of wall thickness to diameter (t/D) and defect depth to thickness (d/t), in predicting failure pressure. These insights help in understanding the underlying mechanisms of pipeline failure and improving design and maintenance strategies.

**Next week**

1. Decide the research topic for the second paper.
2. Write down the introduction part and collect enough literature review.
3. Decide the methodology to establish the model.
4. Collect dataset.

Papers can be found in my github: [https://github.com/cheng-mateng/weeklyupdate](https://github.com/cheng-mateng/weeklyupdate.git)

**Reference**

Al-Sabaeei, A. M., Alhussian, H., Abdulkadir, S. J., & Jagadeesh, A. (2023). Prediction of oil and gas pipeline failures through machine learning approaches: A systematic review. Energy Reports, 10, 1313-1338.

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Lagaros, N. D., & Plevris, V. (2022). Artificial intelligence (AI) applied in civil engineering. *Applied Sciences*, *12*(15), 7595.

Mazumder, R. K., Salman, A. M., & Li, Y. (2021). Failure risk analysis of pipelines using data-driven machine learning algorithms. *Structural safety*, *89*, 102047.

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Xiao, R., Zayed, T., Meguid, M. A., & Sushama, L. (2024). Predicting failure pressure of corroded gas pipelines: a data-driven approach using machine learning. *Process Safety and Environmental Protection*.