

# Neural Networks for Quantitative Resilience Prediction

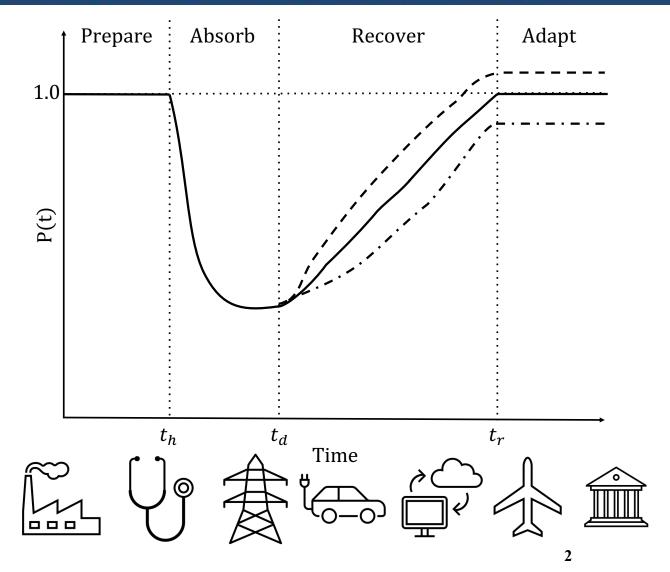
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## Introduction

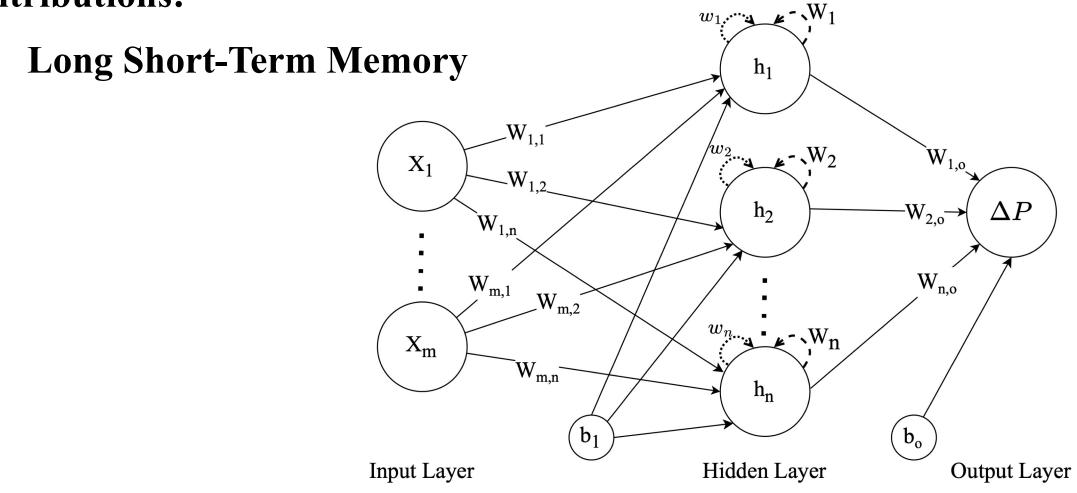
- Relevant past studies
  - Resilience metrics, Markov processes, Bayesian Networks and Petri nets;
  - Multiple Linear Regression with Interaction (MLRI).
  - Mostly, to improve future design or limited to smooth trends.
- Predictive Resilience Modeling
  - Track and predict system resilience including negative and positive factor driving deterioration and recovery in the system performance.
  - A discrete resilience curve incorporating covariates can be described as:

 $P(i) = P(i-1) + \Delta P(i)$ 





**Contributions:** 





#### Model Assessment

- **Predictive Mean Squared Error (PMSE):** computes the mean discrepancy of the model estimates from the actual data considering the test data.
  - Validation Mean Squared Error (VMSE):

Considers the validation data.

- Mean Squared Error (MSE): Considers the entire data.
- Mean Absolute Percentage Error (MAPE): quantifies the mean accuracy of time-dependent problems.
- Adjusted Coefficient of Determination  $(r_{adj}^2)$ : measures the variation in the dependent variable that is explained by the independent variables incorporated into the model.

### **Feature Selection**

There are two steps to select the most relevant subset of covariates:

1. Perform a forward selection search to rank subsets of k covariates according to a heuristic "merit" function:

$$M_s = \frac{k \,\overline{r_{co}}}{\sqrt{k + k(k-1)\overline{r_{cc}}}}$$

2. Create and train models with the highest-ranked subsets of covariates in the previous step. Then, evaluate models and select the one that achieves the highest  $r_{adj}^2$  and smallest overall error.



### **Illustrations:**

Table 1: Covariates collected from January 2020 to November 2022.

| Covariate Name                                       |                        | Covariate Name                           |
|--|------------------------|--|
| $X_1$ Number of Deaths                               | <i>X</i> <sub>11</sub> | Treasury Yield Curve                     |
| $X_2$ Number of Cases                                | <i>X</i> <sub>12</sub> | Standard & Poor's 500 Index Stock Market |
| X <sub>3</sub> Stringency Index                      | <i>X</i> <sub>13</sub> | Durable Goods Orders                     |
| X <sub>4</sub> Workplace closures (policies)         | X <sub>14</sub>        | New Orders Index                         |
| $X_5$ Number of visitors to workplace (%)            | <i>X</i> <sub>15</sub> | Consumer Confidence Index                |
| $X_6$ Consumer Activity (%)                          | <i>X</i> <sub>16</sub> | Federal Funds Rate                       |
| <b>X<sub>7</sub> Unemployment Benefits (million)</b> | <i>X</i> <sub>17</sub> | Mortgage Rate                            |
| $X_8$ Overall population fully vaccinated (%)        | <i>X</i> <sub>18</sub> | Personal Consumption Expenditures        |
| $X_9$ Number of cases in vaccinated people           | <i>X</i> <sub>19</sub> | Industrial Production                    |
| $X_{10}$ Face covering (policies)                    | P                      | COVID-19 US nonfarm jobs                 |



#### **Illustrations:**

Table 2: Results of 1<sup>st</sup> step of<br/>feature selection:

| Feature Subset             | k | M <sub>s</sub> |
|----------------------------|---|----------------|
| X <sub>19</sub>            | 1 | 0.5567882      |
| $X_{19}, X_{14}$           | 2 | 0.6151150      |
| $X_{19}, X_{14}, X_4$      | 3 | 0.6257571      |
| $X_{19}, X_{14}, X_4, X_7$ | 4 | 0.6208308      |

#### Table 3: NN hyperparameters:

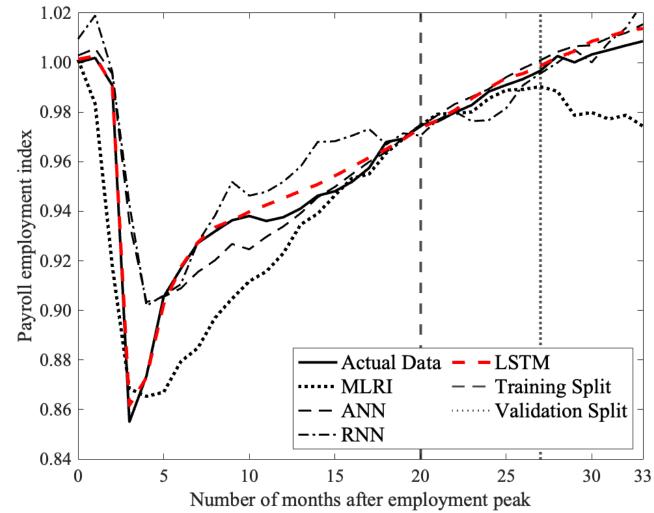
| Optimizer                   | Adam |
|-----------------------------|------|
| Learning Rate               | 0.01 |
| Neurons in the hidden layer | 1 15 |
| Max. number of Epochs       | 1000 |
| Earlier Stopping Condition  | Yes  |

Table 4: Results of  $2^{nd}$  step of feature selection:

| Model                | Training<br>Split | MLRI             | RI ANN RNN            |                            | LSTM                       |
|----------------------|-------------------|------------------|-----------------------|----------------------------|----------------------------|
| Covariates<br>Subset |                   | $X_{19}, X_{14}$ | $X_{19}, X_{14}, X_4$ | $X_{19}, X_{14}, X_4, X_7$ | $X_{19}, X_{14}, X_4, X_7$ |
| Neurons              |                   | -                | 3                     | 12                         | 7                          |
| DMCE                 | 60                | 0.0002884        | 0.0000247             | 0.0000498                  | 0.0000205                  |
| PMSE                 | 70                | 0.0004306        | 0.0000731             | 0.0001766                  | 0.000006                   |
| VMSE                 | 60                | -                | 0.0000085             | 0.0000415                  | 0.0000035                  |
| VIVISE               | 70                | -                | 0.0000094             | 0.0000182                  | 0.0000031                  |
| MCE                  | 60                | 0.000538         | 0.000245              | 0.000355                   | 0.000015                   |
| MSE                  | 70                | 0.000553         | 0.000272              | 0.000320                   | 0.000017                   |
| MAPE                 | 60                | 1.70             | 0.81                  | 1.21                       | 0.32                       |
|                      | 70                | 1.73             | 0.81                  | 1.05                       | 0.29                       |
| $r_{adj}^2$          | 60                | 0.6087           | 0.8154                | 0.7241                     | 0.9885                     |
|                      | 70                | 0.5978           | 0.7952                | 0.7512                     | 0.9867                     |
| Average              | 60                | -                | 546                   | 406                        | 641                        |
| Epochs               | 70                | -                | 609                   | 457                        | 598                        |



**Illustrations:** Figure 1: Model fit of best models using 60% of the data for training.



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## Conclusion

- Summary
  - Presented three alternative neural network models, including ANN, RNN and LSTM, to model and predict system resilience considering disruptive events and restorative activities that characterize the degradation and recovery in the system performance.
- Results
  - Neural network approaches can accurately and efficiently track and predict system resilience finding application in many domains;
  - All proposed approaches outperformed the MLRI model;
  - LSTMs exhibited an improvement of over 60% in the  $r_{adj}^2$  and a 34.07-fold reduction in the predictive error (PMSE).
- Future Research
  - Explore more challenging data sets including multiple shocks and different applications.
  - Apply alternative neural network model such as Gated Recurrent Units.



# Thank you!