Machine Learning for Layout optimization of Braces of Building Frames

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Background

- Seismic retrofit of building frames.
- Add braces to upgrade stiffness.
- Increase of stress in existing beams and columns.
- Optimal locations of braces considering effect on existing members



Difficulty in combinatorial problems

- Combinatorial problem:
 - Difficult to use mathematical programming.
 - Use heuristics.
 - Large computational cost for problem with many variables.

Use machine learning for reduction of computational cost.

Support vector machine (SVM)

- Classification to 2 classes
- Linear or nonlinear (Gauss) kernel



Binary decision tree

- Classification to multiple classes
- Regression tree for numeric attribute



<u>Application of machine learning to</u> <u>structural optimization</u>

- Neural network for prediction (approximation) of structural responses
- Optimal member grouping
- Optimal parameters for heuristics
- Shape optimization of periodic structures
- Learning features of feasible solutions
- Optimal search region/direction in heuristic approach

Optimization of brace locations

- Plane steel frame
- Algorithm: simulated annealing (SA)
- Five patters of braces



- Consider sensmic retrofit
 - → Fix cross-sections of beams and columns Optimize patterns and locations of braces

Design variables

• Five patterns denoted by x = 1,2,3,4,5 $y = (y_1, y_2, y_3, ..., y_m), (y_i \in \{1,2,3,4,5\})$

• Number of locations = 15





Optimization problem

• Objective function:

minimize maximum stress σ_{max} of beams and columns

• Constraints:

interstory drift angle $\delta_{max} \leq 0.005$ number of braces in each story ≤ 2

Simulated annealing (SA)

1. Randomly generate initial solution.

 $P_r = \exp\left(-\frac{\Delta F}{cT}\right)$

- 2. Randomly generate neighborhood solutions and select their best solution. Select the best solution with probabilistically even it does not improve the objective value.
- 3. Reduce the temperature parameter if the termination condition is not satisfied and go to 2.

Outline of SA



Neighborhood solutions

Preprocessing: binarization

- SVM handles only ordered variables
 → binarization using dummy variables
- Integer variable $y_i \in \{1,2,3,4,5\}$ is converted to five dummy binary variables $x_{i1}, x_{i2}, x_{i3}, x_{i4}, x_{i5} \in \{0,1\}$



Preprocessigng: convolution

- Relation to neighboring brace is important
 - \rightarrow Filtering by convolution
- Convolution:

Extract features applying filters to original data



Preprocessign: pooling

- Increase of number of variables by convolution
 - \rightarrow Reduc variables by pooling
- Example: combine two same features in the same story.



Accuracy of learning

- Label +1: Approximate optimal
- Label –1: Non-optimal
- Small ratio of 'False-Negative'
 - \rightarrow High accuracy of learning



Optimization result

- 5-story 3-span frame
- Story height: 4 m, Depth 6 m
- No. of steps: 1000
 No. of neighborhood solutions: 50 Initial temperature: 1.0
 Temperature reduction ratio: 0.99

13 14 15 4 m P_{5} 10 11 12 4 m 8 9 7 4 m P_3 5 6 4 4 m P_2 2 3 1 4 m 6 m 6 m 6 m

Analysis model

- Use OpenSees for analysis
- Beam-Column element for all members
- Pin-support at column base
- Apply only horizontal loads calculated from Japanese building regulation
- Model rigid floor by multiplying axial stiffness of beam by 10
- Assign large stiffness for base beam

Optimization problem

• Objective function:

minimize maximum stress σ_{max} of beams and columns

• Constraints:

interstory drift angle $\delta_{max} \leq 0.005$ number of braces in each story ≤ 2

• Select the beat solution among 20 trials of SA

Optimal solution





	σ _{max} (N/mm²)	$\theta_{\sf max}$	V (m³)
No brace	649.54	0.0220	0
Optimal	84.83	0.0019	0.35

Comparison to standard layout

• Optimal solution is better than standard layout







Pattern A



Pattern C

	σ _{max} (N/mm²)	$\theta_{\sf max}$	V (m³)
Pattern A	169.32	0.0028	0.27
Pattern B	221.82	0.0034	0.18
Pattern C	118.57	0.0016	0.37
Optimal	84.83	0.0019	0.35

Learning for 2 classes

- Randomly generate 10000 solutions
- Approximate optimal: top 10% solutions
 Non-optimal: worst 10% solutions

Five strategies for convolution and pooling





Learning for 2 classes

• Two types of filters



Filter 4 (exclude no-brace): 4 x 4 x 4 = 64 patterns Filter 5 (exclude no-brace): 5 x 5 x 4 = 100 patterns

Learning results by SVM

	Flter 4		Filter 5			
	Error	FN	FP	Error	FN	FP
S1	0.0250	17/1000	35/1000	0.0250	17/1000	35/1000
S2	0.0410	41/1000	28/1000	0.0110	10/1000	10/1000
S 3	0.0560	64/1000	28/1000	0.0120	15/1000	18/1000
S4	0.1495	133/1000	144/1000	0.0385	26/1000	57/1000
S 5	0.2050	194/1000	221/1000	0.0965	107/1000	106/1000

Learning result by SVM

• Calculation of score

$$S(x) = \frac{1}{a} \cdot \boldsymbol{\beta} \cdot \boldsymbol{x} + \boldsymbol{b}$$
$$\boldsymbol{\beta} = (\beta_1, \dots, \beta_m) \quad : \text{ coefficient vector}$$

- If β_i is large (positive), $x_i = 1$ contributes to approximate optimal solution.
- If β_i is small (negative), $x_i = 1$ contributes to non-optimal solution.

Filters characterizing approximate optimal solutions



Filters characterizing non-optimal solutions





Learning results by BDT

	Flter 4			Filter 5		
	Error	FN	FP	Error	FN	FP
S1	0.0390	38/1000	40/1000	0.0390	38/1000	40/1000
S2	0.0725	65/1000	63/1000	0.0290	33/1000	21/1000
S 3	0.0920	76/1000	73/1000	0.0340	24/1000	24/1000
S4	0.2309	317/1000	107/1000	0.0930	83/1000	95/1000
S5	0.3413	407/1000	263/1000	0.2194	170/1000	250/1000

Feature tree by BDT



SA with machine learning



<u>Comparison of computational time</u>

		SA	SVM	BDT
Learning	Analysis (s)		2093	2093
	Learning (s)		12.4	6.1
Optimization	Prediction (s)		483.7	360.5
	Analysis (s)	14314.3	7961.6	7162.6
	Optimization incl. learning (s)	14314.3	10550.7	9622.2
	Number of analyses	67368	35710	27819
	Optimal	84.83	87.08	87.51
	objective value	N/mm ²	N/mm ²	N/mm ²

Optimization result







SA

SA with SVM

SA with BDT

Conclusions

- A method based on SA for optimization of brace locations of building frames.
- Minimize maximum additional stress of beams and columns under horizontal static loads representing seismic loads.
- Distinct classification of approximate optimal and nonoptimal solutions is effective to improve the accuracy of learning and prediction.
- Convolution using filters with 'no brace' generally improves the accuracy of prediction; however, it increases the computational cost.
- Pooling in each of lower stories is effective to reduce the number of variables, while maintaining the accuracy.

Conclusions

- Computational cost can be successfully reduced using BDT or SVM for detecting non-optimal solutions during optimization.
- Properties of approximate optimal and nonoptimal solutions can be extracted from the feature trees as an output of BDT and the coefficients of the function for estimating the score of SVM.
- Braces should be continuously located to reduce the additional stresses in beams and columns due to horizontal seismic loads.