The Diminishing Returns of Forecasting Models' Complexity in Industrial Applications

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Research Hypothesis / Assumptions

- Complex Models vs. System Performance

  Predictive models focus on **specific** system components. Yet they may not significantly impact **overall** system performance.

- Internal Variability

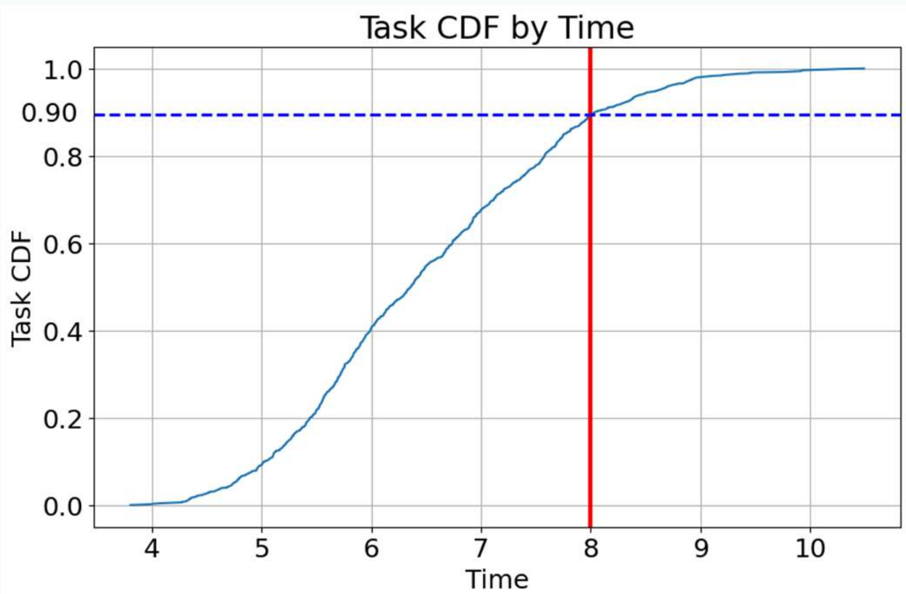
  Real-system complexity introduces variability that diminishes advantages of sophisticated models.

- Tailored Implementation

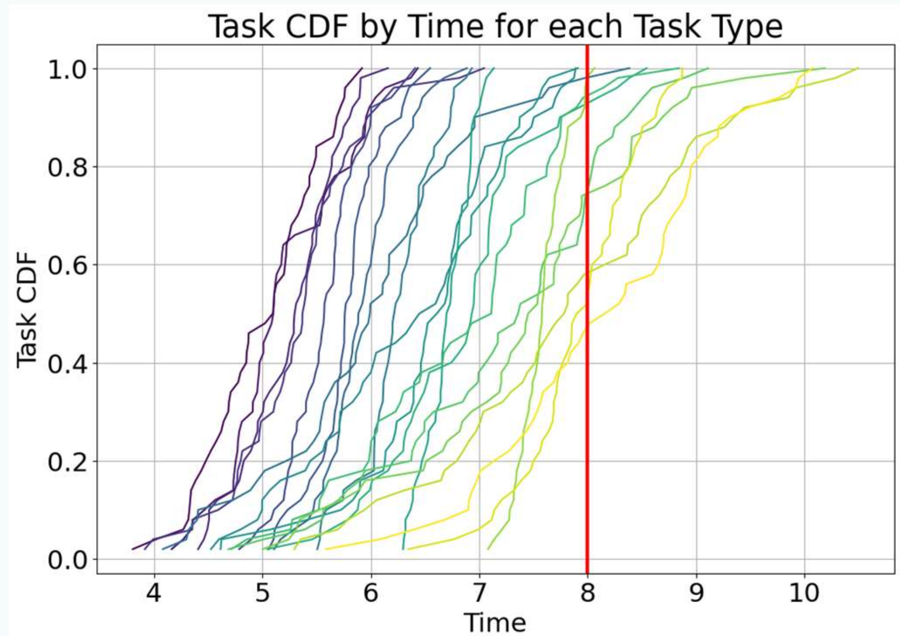
  Tools must be matched to specific goals and working environments.

Example / Motivation

- Worker has daily task that must be finished within 8 hours in order to be consider as succesful. She wants to better schedule her tasks.



R^2=0.632



A Good **prediction** but no help in **scheduling** (assuming all tasks are needed).

Prediction (Regression) Models – Literature review

- Machine Learning Approaches
  - Decision Tree (DT)
  - Adaptive Boosting model (AdaBoost)
  - Logistic Regression (LR)
  - Stochastic Gradient Descent (SGD)
  - Random Forest (RF)
  - Gradient Boosting classifier (GBM)
  - Extra Tree Classifier (ETC)
  - Gaussian Naive Bayes (G-NB)
  - Support Vector Machine (SVM)

- Deep Learning Methods
  - Deep Convolutional Neural Networks (DCNN)
  - Generative Adversarial Network (GAN)
  - Sequential model
  - And more…

Prediction (Regression) Models – Literature review

- Common Prediction Metrics
  - R-squared (R^2)
  - Mean Absolute Error (MAE)
  - Mean Squared Error (MSE)
  - Root Mean Squared Error (RMSE)
  - Mean Absolute Percentage Error (MAPE)

- Machine Learning Applications
  - Scheduling and resource allocation
  - Process monitoring and KPI tracking
  - Quality prediction and improvement
  - Maintenance needs identification

Research Methodology

1. System Analysis:
   Identify what needs to be predicted to improve system performance.
2. Metric Selection:
   Determine crucial operational metrics for the organization.
3. Tool Selection:
   Choose appropriate prediction tools with varying complexity levels.
4. Problem Solving:
   Apply prediction estimators and calculate system performance.
5. Comparison:
   Compare performance across different complexity levels.

Case Study Design

- Data Generation

  32 production duration groups (5 Boolean columns) across 100,000 items. Normal distribution with varying means and standard deviations starting from ({20,0.5},{10,2}) and increase by steps. 5 dummy Boolean columns (to allow overfitting).

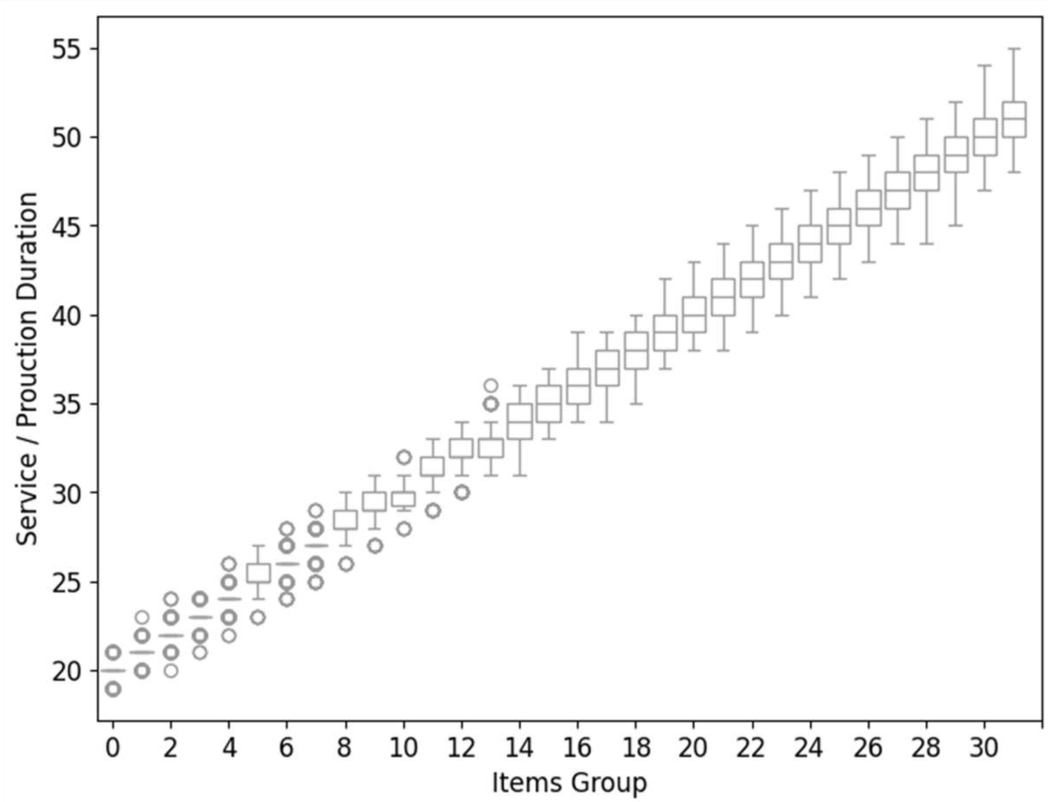
- Predictive Models

  - **Decision Tree Model**: Full tree generated and pruned to varying sizes. Predictions saved for each item across all tree sizes
  - **Deep Learning Model**: Performed deep learning training with a range of training iterations (epochs) to optimize model performance

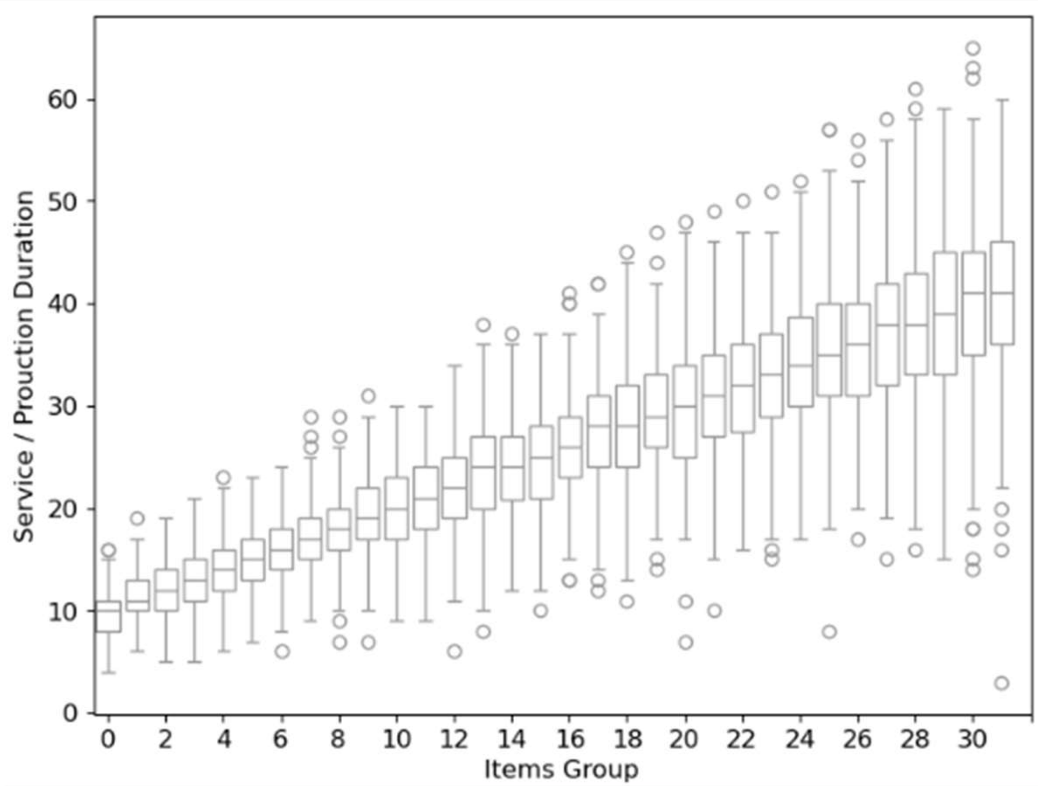
- Performance evaluation to minimize average waiting time (SPT – shortest process time first): Random selection of 10 Items. Sorting by expected duration. 1000 replications (items mix).

Item Duration Distribution

<u>Low Variability</u> (μ=20, σ=0.5)



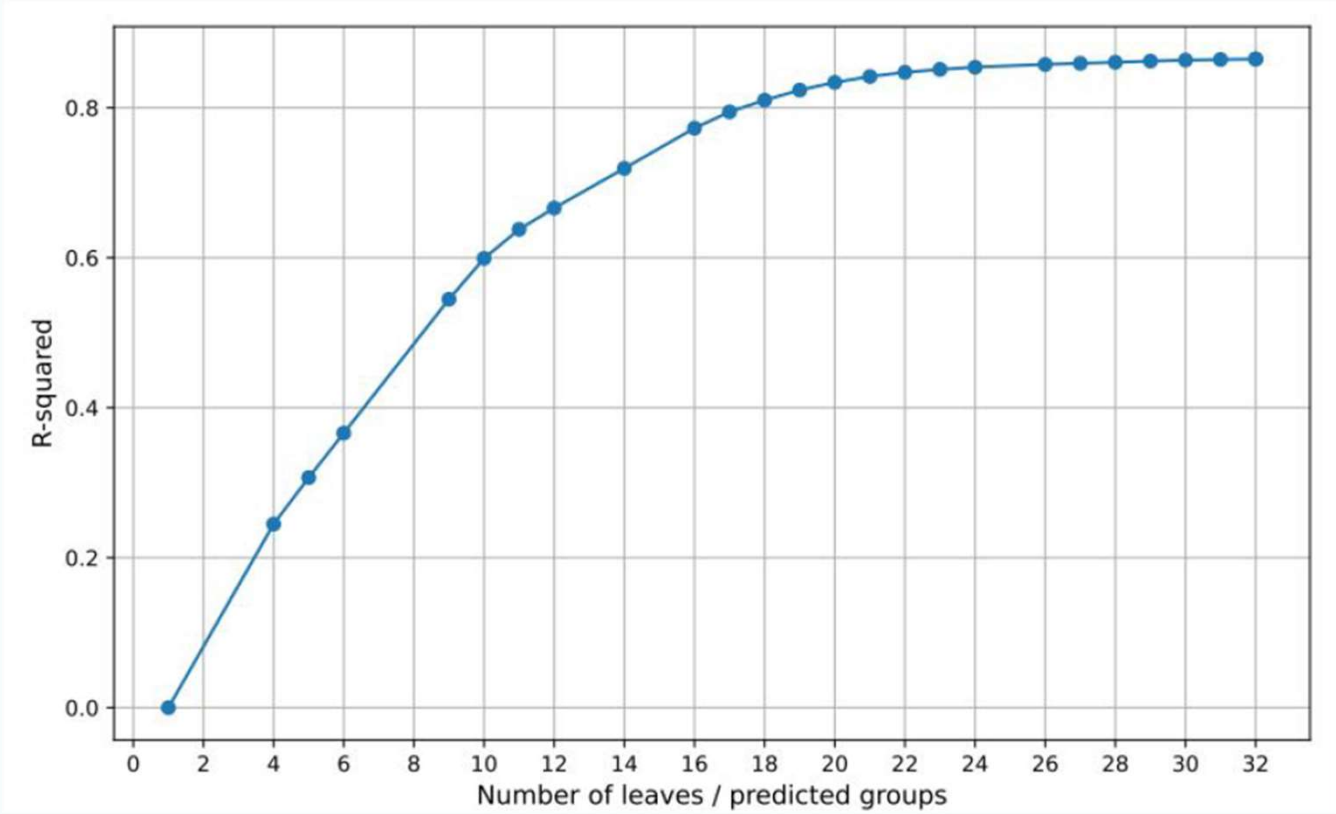
<u>High Variability</u> (μ=10, σ=2)



Model Complexity vs. Accuracy - Diminishing Returns

Decision Tree Model

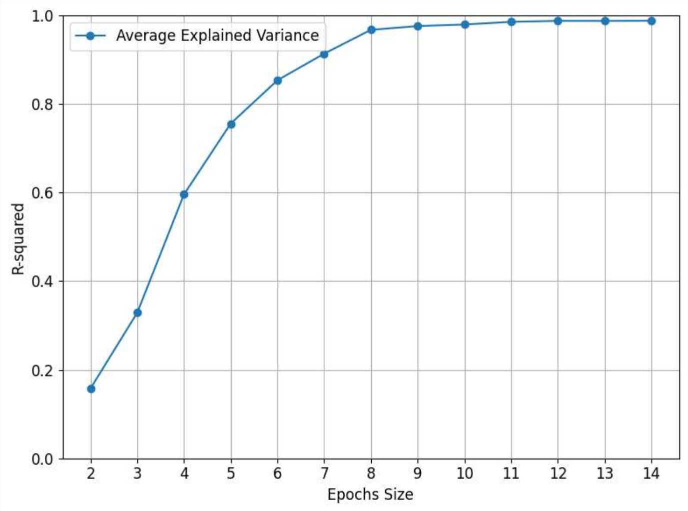
R-squared increases with model complexity. (number of leaves) But gains diminish after certain threshold.

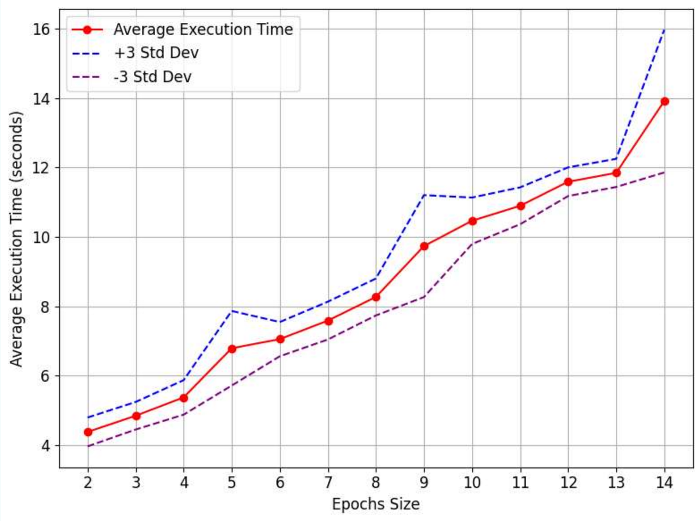


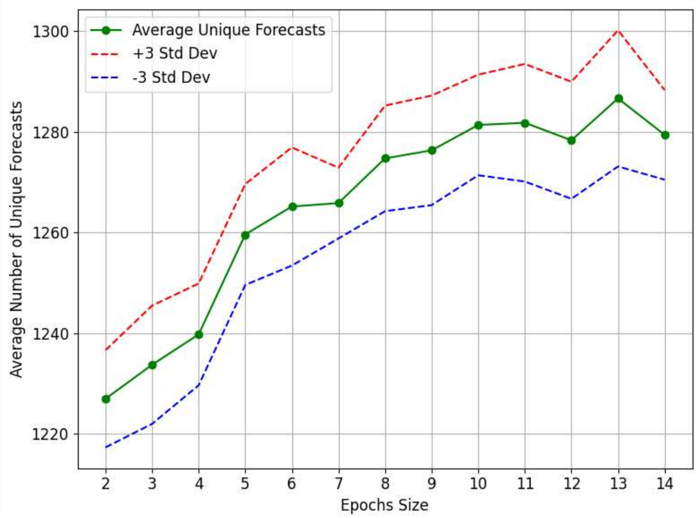
Model Complexity vs. Accuracy - Diminishing Returns

Deep Learning Model

- R-squared increases with model complexity (number of training rounds). But gains diminish after certain threshold.
- Number of training rounds takes more time and more "predictors"
- (25 repetitions)







Waiting Time Evaluation (simple example with 4 items)

Index	F1	F2	D
1	21	18	20
2	26	28	30
3	20	22	35
4	32	25	25

Sort by F1

Index	F1	F2	D	X
3	20	22	35	3
1	21	18	20	2
2	26	28	30	1
4	32	25	25	0

Waiting Time (F1) = 3*35+2*20+1*30+0*25= 175

Sort by F2

Index	F1	F2	D	X
1	21	18	20	3
3	20	22	35	2
4	32	25	25	1
2	26	28	30	0

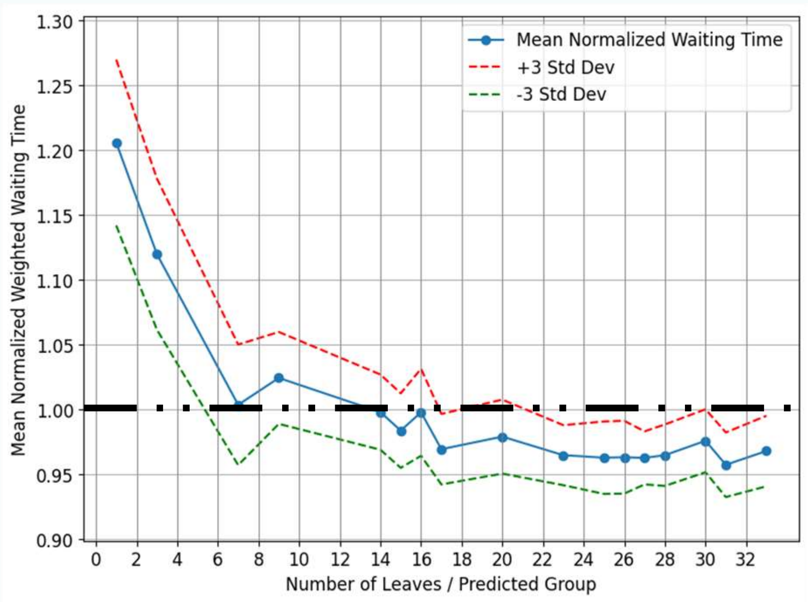
Waiting Time (F2) = 3*20+2*35+1*25+0*30= 155

Waiting Time(mean)=(175+155)/2=165
⇒ Norm Waiting Time (F1)= 175/165=1.06
⇒ Norm Waiting Time (F2)= 155/165=0.94

F1- Forecast 1
F2 – Forecast 2
D – Actual Duration
X – delayed items

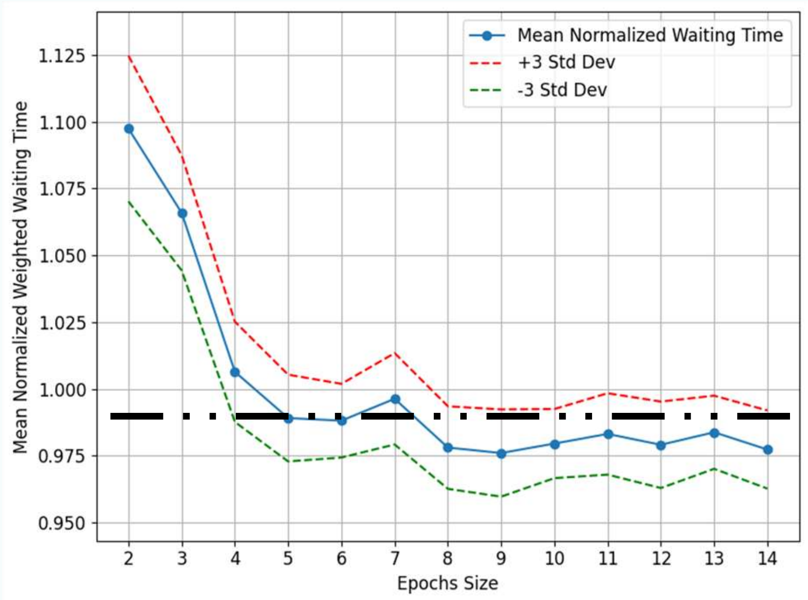
Waiting Time Results - High Variability Environment (μ=10, σ=2)

Decision Tree Model



Statistical significance only in configurations with **2 groups** or fewer.

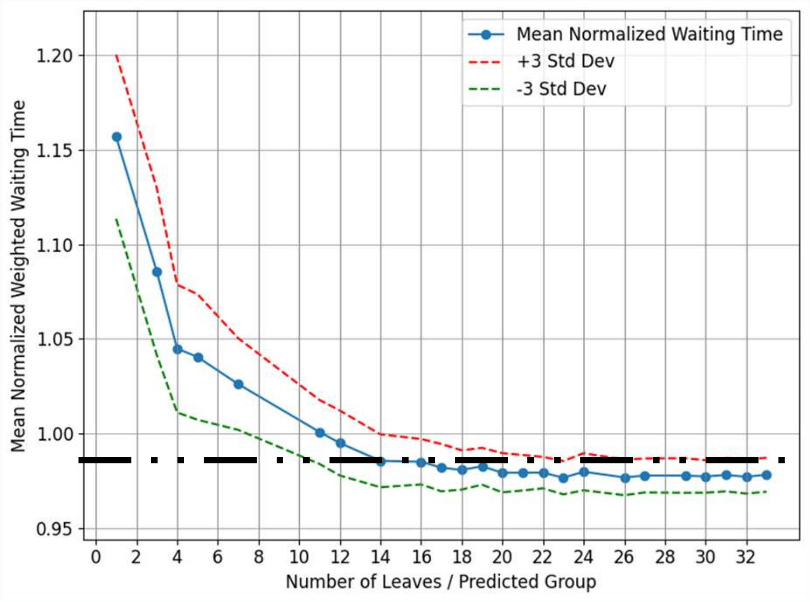
Deep Learning Model



Statistical significance only in configurations with **3 rounds** or fewer.

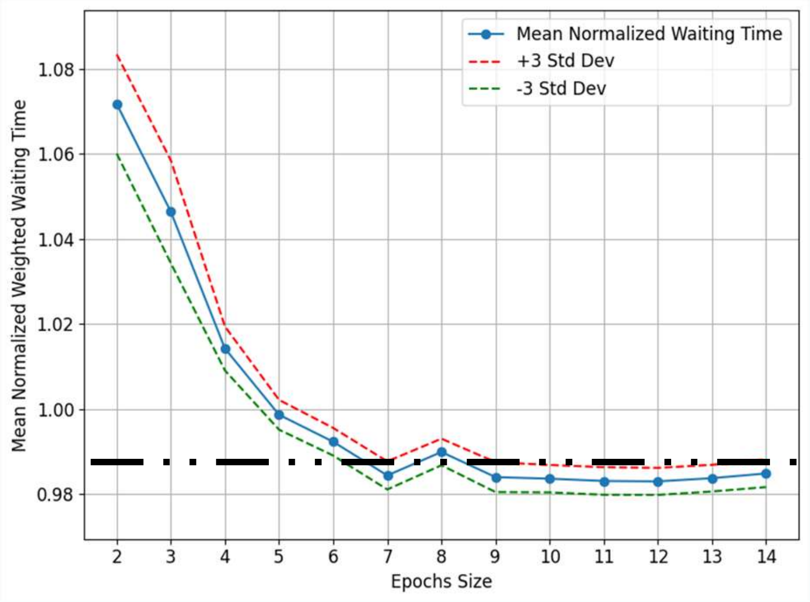
Waiting Time Results - Low Variability Environment (μ=20, σ=0.2)

Decision Tree Model



Statistical significance only in configurations with **6 groups** or fewer.

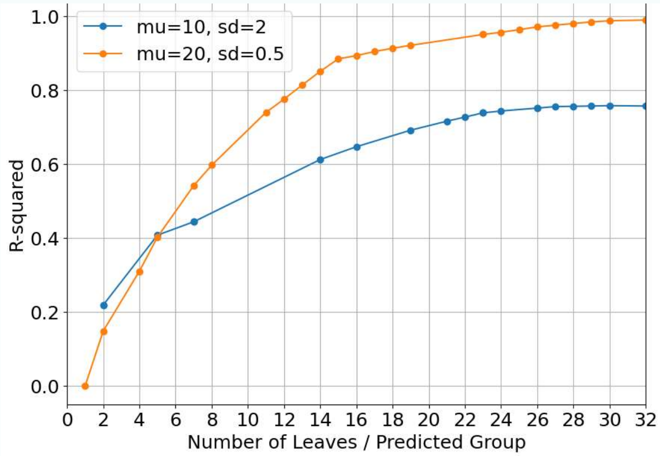
Deep Learning Model

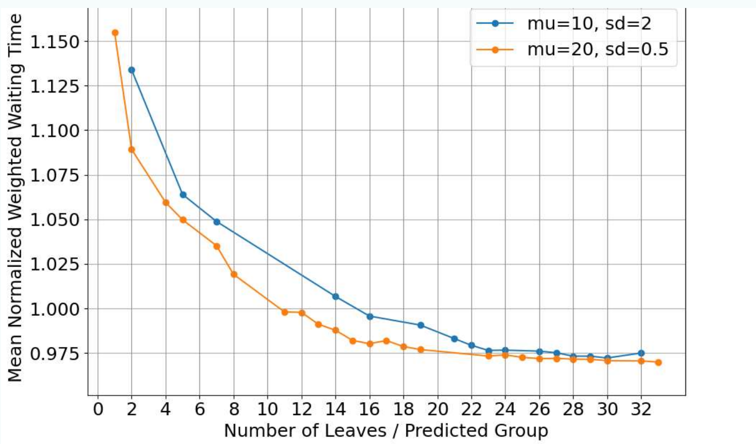


Statistical significance only in configurations with **6 rounds** or fewer.

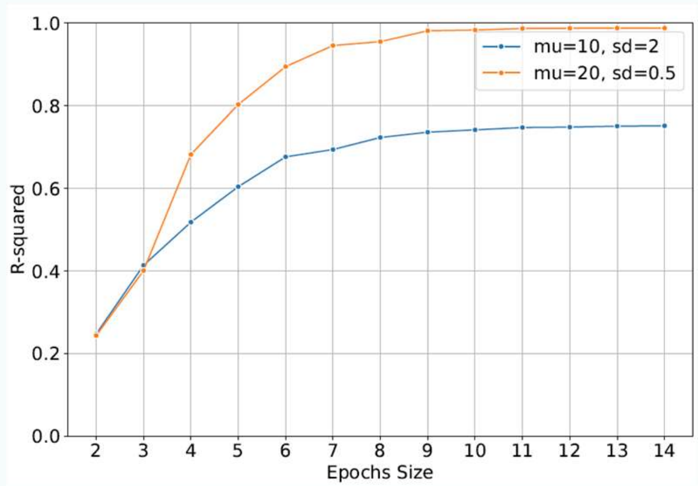
Waiting Time Results - by Variability Environment (summary)

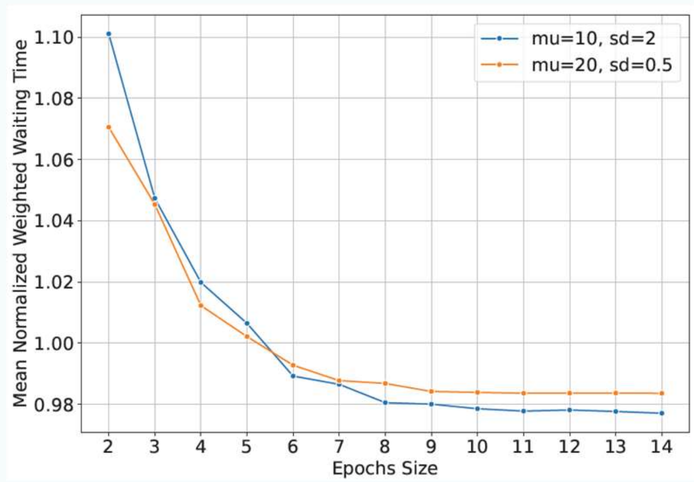
Decision Tree Model





Deep Learning Model





Insights:

- Higher R^2 in a low variability environment.
- Deep learning “complex” models impact wait time more in high variability environment.
- The decision tree impact wait time more in low variability environment.

Research Implications

- Bridging the Gap

  Connects statistical solutions with business impact for complex systems.

- Practical Guidelines

  Guide practitioners toward appropriate tools based on system characteristics.

- Integration Innovation

  Combining prediction, optimization, and simulation creates innovative operational

Thank You for your attention!

Code used in this presentation:
Deep Leaning Model
https://drive.google.com/file/d/1lIWld9MM8w8alPQKbjEurV0FySFXEe6Q/view?usp=sharing
Decision Tree (CART):
https://drive.google.com/file/d/1ktlzY8I_TobeobRGbHw2pAjBWt2MmDCo/view?usp=sharing

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