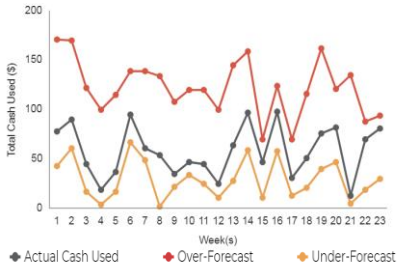
A Novel Approach to Align Forecasts to Competing Operational Business Outcomes

ABSTRACT

We develop an approach that quantities credit union's cash-on-hand forecasts and identifies the set of predictions among a set of competing models that balances competing KPIs among the Chief Membership Engagement Officer (CMEO) and Chief Financial Officer (CFO). This poster intends to demonstrate 1) how our forecast aligns to a couple custom business KPIs agreed upon among the CMEO and CFO, 2) how any model forecast could be evaluated from these business perspective metrics, and 3) a tool that the credit union can use in practice.

INTRODUCTION

The motivation for our study is that if a business tries to identify a model with the lowest prediction error, the "best" forecast could be different based on the error metric used. Furthermore, even using the same error metric, demand forecasts that have the same overall statistical performance will likely not yield the same business performance.



❖ The example forecasts above (Over-, Under-, and Balanced-) all have the same SMAPE of 75.

Research Questions:

❖ Can we develop a methodology that aligns statistical metrics and competing business KPIs?

❖ Can we develop a software tool that the credit union can use to identify the best forecast to deploy in practice?

METHODOLOGY

Model Development

Explanatory Data Analysis → Data Preprocessing → Cross Validation → Model Selection → Model Formation

Analytical Hierarchy Process (AHP)

Six Potential Model:

- **S** Stacked Ensemble (H_2O)
- **P** Prophet
- **X** XGBoost
- **N** nnetar (Neural Network)
- **T** TBATS
- **A** ARIMA

Criteria for Model Comparisons:

- MAE
- RMSE
- MAPE
- SMAPE (1)
- SMAPE (2)
- Decision Maker Metrics ($)

STEP 1: Pairwise Comparison Matrix

Use a pairwise comparison, meaning two alternatives are compared according to a criterion and one is preferred.

STEP 2: Normalize to Synthesize

- Normalize the matrices.
- Prioritize the decision alternatives within each criterion.

STEP 3: Criteria Preference Matrix

Combine preference vectors:

	Criteria					
Model	MAE	RMSE	MAPE	SMAPE1	SMAPE2	Cost
S	0.139106	0.151247	0.178751	0.144988	0.090705	0.134144
P	0.157563	0.15985	0.199547	0.15429	0.177825	0.163961
X	0.208461	0.193085	0.105645	0.214831	0.234595	0.194808
N	0.141732	0.155605	0.152923	0.154205	0.207922	0.160665
T	0.175623	0.17018	0.177489	0.165697	0.08575	0.177354
A	0.177515	0.170034	0.185646	0.165989	0.203203	0.169067

STEP 4: Rank Criteria

Rank the criteria based on its relative importance to the decision markers.

STEP 5: Normalize Ranked Criteria

Normalize the criteria matrix from step 4.

STEP 6: Preference Vector for the Criteria

Calculate the preference vector for the criteria:

Criteria	MAE	RMSE	MAPE	SMAPE1	SMAPE2	Cost
Preference Vector	0.034274	0.034274	0.073628	0.140313	0.462549	0.254963

STEP 7: Overall Scores and Overall Ranking

Overall Scores

Model	Overall Score
S	0.1196
P	0.1713
X	0.2099
N	0.1802
T	0.1331
A	0.1859
Total:	1.0000

Overall Ranking

Ranking	Model:
1	Stacked Ensemble
2	TBATS
3	Prophet
4	nnetar
5	ARIMA
6	XGBoost

STUDY IMPLICATIONS

We developed a Shiny App in R for the deployment of TCU. By using our model evaluation App, the credit union can:

❖ Customize backorder cost and interest rate parameters.

❖ Identify the best forecasting model among a set of competing models, even when statistical metrics Might conflict.

❖ Lead to better business outcomes among competing decision makers.



CONCLUSION

❖ Our methodology can be widely used in other businesses in need of a model evaluation mechanism.

❖ We have successfully developed a practical tool to evaluate different potential models in order to identify the "best" forecast.

❖ "Your brilliant work will enable TCU to reach targets, provide our team members with valuable resources, which will enable us to provide consistent WOW service to our members. Great work!"

--- Nicole Alcorn, CMEO of TCU