An Extreme-Adaptive Time Series Prediction Model Based on Probability-Enhanced LSTM Neural Networks

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Problem: Univariate Time Series with Extreme Events Forecasting

$$[X_1, X_2, \ldots, X_T] \in R^T \rightarrow [X_{T+1}, \ldots, X_{T+H}], \in R^H$$

Challenges:

- Most values are normal and contribute significantly to the overall prediction performance
- Few extreme values but they must be precisely forecasted to avoid disastrous events

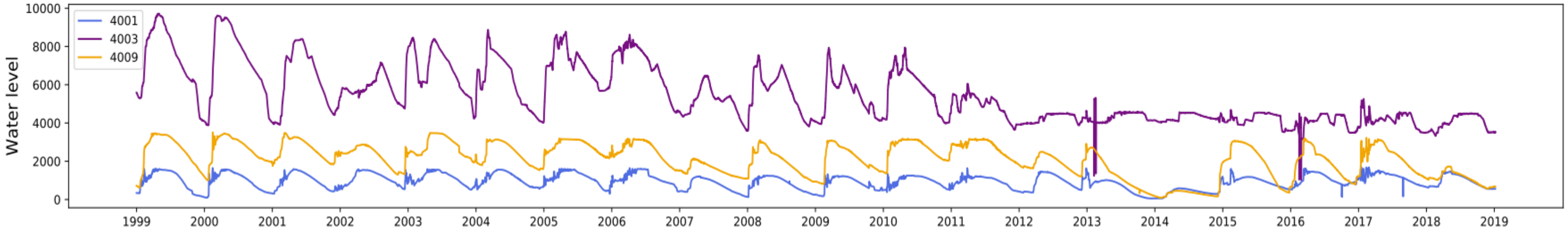
Goal:

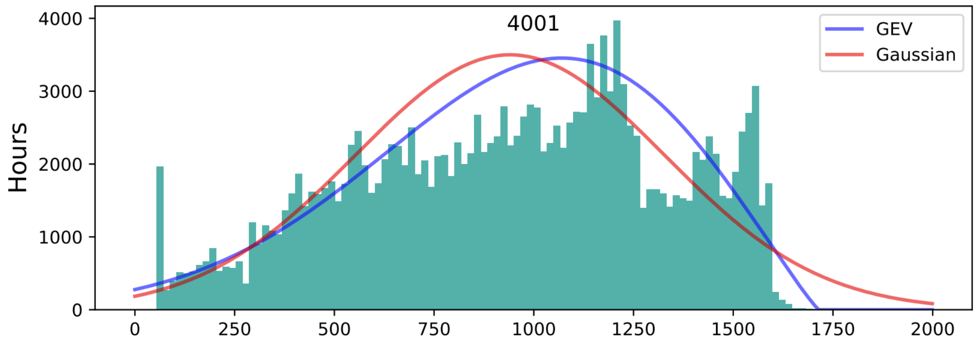
- A model that concurrently learns extreme and normal prediction functions
- Long sequence forecasting
- Good generalization

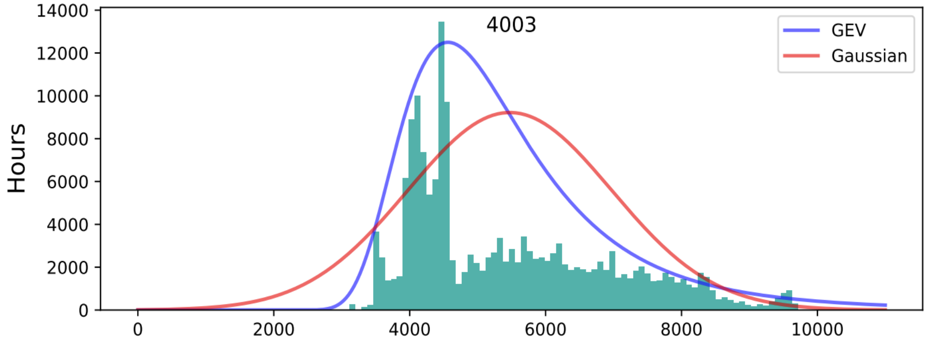
Dataset:

- We evaluate the proposed model on the difficult 3-day ahead hourly water level prediction task applied to 9 reservoirs in California

Extreme Events:







GEV (Generalized Extreme Value) distribution provides a better fit, showing the presence of extreme values in our data,

$$F(x;\mu,\sigma,\xi) = \exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-1/\xi}\right\}, \quad (1)$$

where $\mu \in \mathbb{R}$, $\sigma > 0$, and ξ are the location, scale, and shape parameters, respectively, conditioned on $1+\xi(x-\mu)/\sigma > 0$.

Motivation: achieving the best overall prediction performance, without sacrificing either the quality of normal or of extreme predictions.

Root Mean Square Error ***(RMSE)***

Mean Absolute Percentage Error ***(MAPE)***

Proposed Methods:

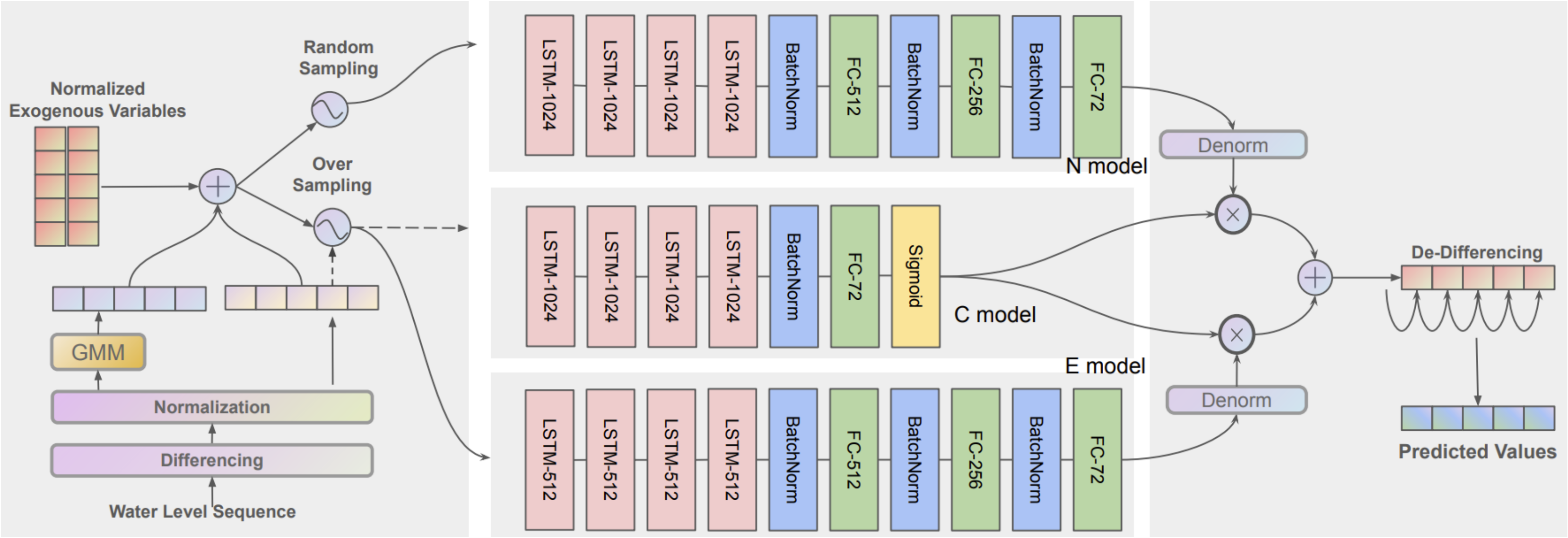
NEC framework: a framework to account for the distribution shift between normal and extreme values; composed of a ***N****ormal*, an ***E****xtreme*, and a ***C****lassification* model.

GMM Indicator: an unsupervised clustering approach to dynamically produce distribution indicators, which improves the model's robustness to the occurrence of severe events.

Selected Backpropagation: helps the models learn the positions and values of appropriate normal or extreme data better.

Parameterized Loss Function: helps our classifier better distinguish event severity.

NEC framework :

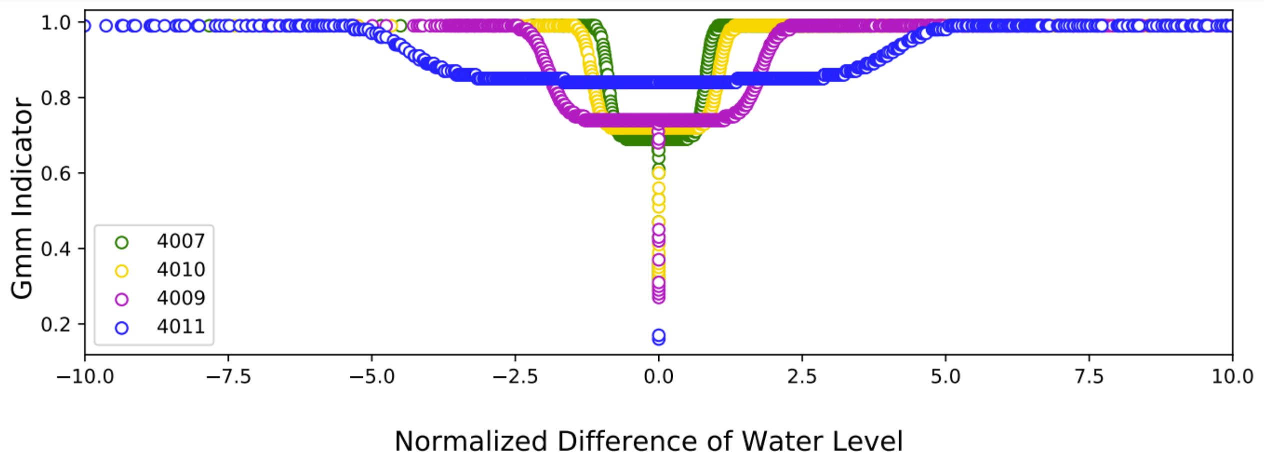


NEC is composed of three separate models, which can be trained in parallel:

- The **Normal** (N) model is trained to best fit normal values in the time series.
- The **Extreme** (E) model is trained to best fit extreme time series values.
- The **Classifier** (C) model is trained to detect when a certain value may be categorized as normal or extreme.

NEC is a purely single variate model; **NEC+** uses optional exogeneous other inputs.

GMM Indicator :



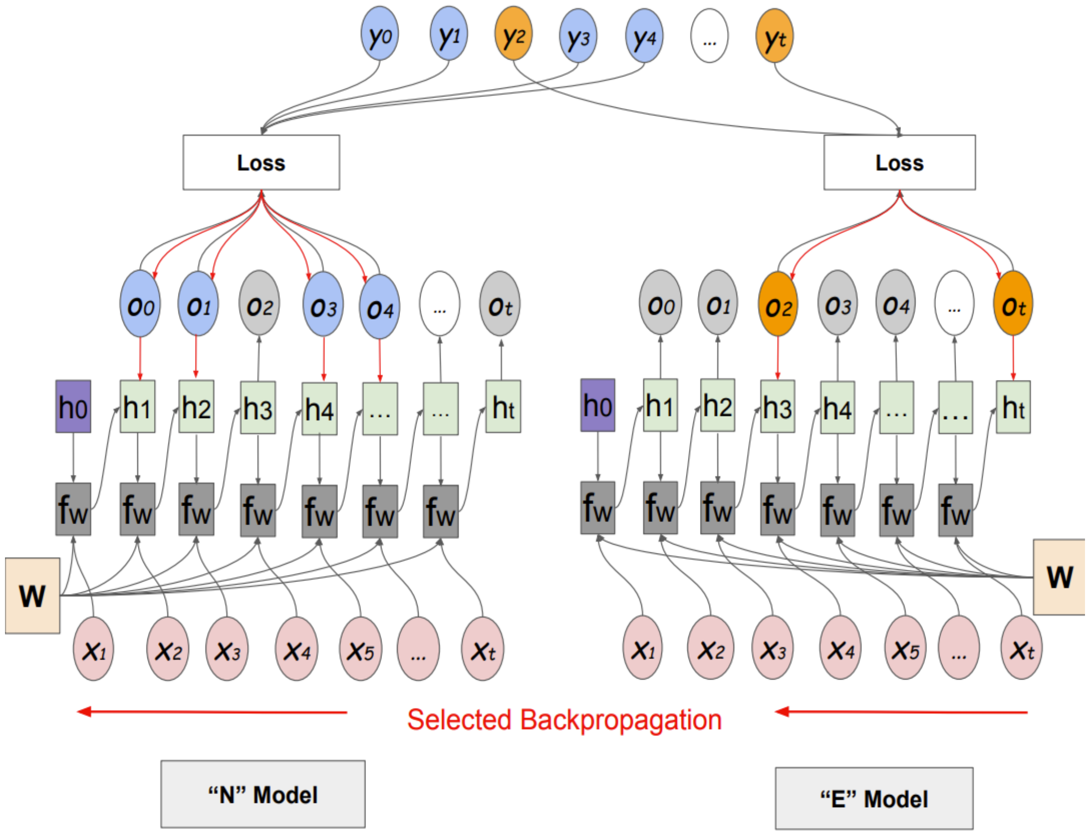
A Gaussian mixture model (GMM) is a weighted sum of M component Gaussian densities,

$$p(x|\lambda) = \sum_{i=1}^{M} w_i g(x|\mu_i, \textstyle\sum i) \ ,$$

where x is a D-dimensional continuous-valued vector, w_i ∀i = 1, . . . , M are the mixture weights, and $g(x|\mu_i, \sum i)$ are the component Gaussian densities.

We compute an indicator feature as the weighted sum of all component probabilities, given the weights learned when fitting the GMM model.

Selected Backpropagation :



Two-stage sampling policy:

1) randomly sample subsections of length $h + f$ from the series to use in training our models

2) perform stratified sampling of regions with and without extreme values, allowing the E and C models to oversample up to OS% samples with at least 1 extreme value in the prediction zone.

Selected Backpropagation:

N model: only normal values add to the loss;

E model: only extreme values add to the loss.

Parameterized Loss Function:

$$BCE(t, p) = -(t \times \log(p) + (1 - t) \times \log(1 - p))$$

$$L = \beta \times BCE(t, p^{\alpha}) + (1 - \beta) \times RMSE(t, p)$$

where α and β are parameters that can be tuned. Values $\alpha > 1$ cause the model to predict p values that are higher in general in order to minimize the distance between t and p^{α}.

Problem: for datasets with a high imbalance between the two classes, BCE will favor the prominent class.

- The BCE part: can be thought of as a blunt instrument that grossly exaggerates all miss-classifications in order to more accurately predict the obscure class
- The RMSE part: allows for a more gentle penalty based on the distance between t and p.

Research Questions:

1. What is the effect of adding the GMM indicator to a model?
2. What is the effect of introducing exogenous features?
3. How do the loss function parameters affect performance?
4. How does NEC+ compare against state-of-the-art baselines?

Baselines:

- **ARIMA**
- **Facebook Prophet**
- **LSTM**
- **DNN-U**: univariate state-of-the-art LSTM-based encoder-decoder hydrologic model.
- **Attention-LSTM**: a state-of-the-art hydrologic model for stream-flow prediction.
- **N-BEATS**: a state-of-the-art time series prediction method that

outperformed all competitors on the standard M3, M4 and TOURISM datasets.

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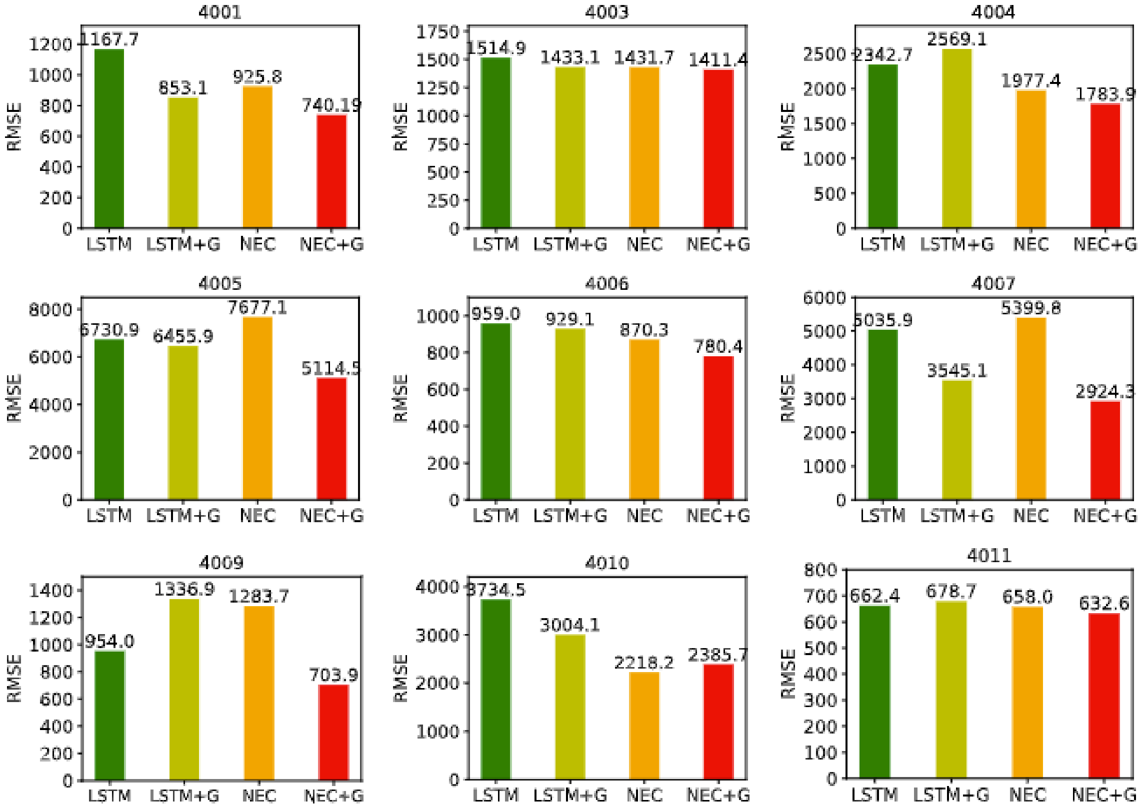
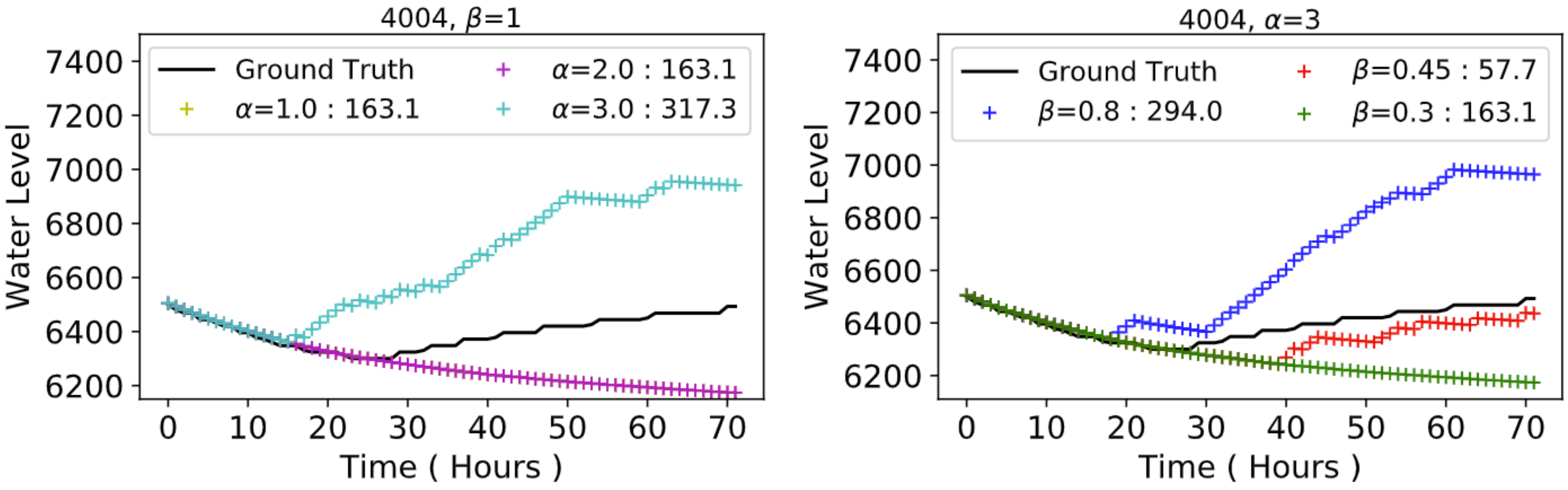


Model/Reservoir	**4005**	**4007**	**4010**
LSTM	6730.93	5035.91	3734.53
LSTM+W	7568.68	5728.30	4145.16
LSTM+G	6455.90	3545.19	3004.14
LSTM+G+W	9760.62	4128.37	2602.58
NEC+G	5114.49	2924.30	2385.77
NEC+G+W (NEC+)	**4352.74**	**2092.73**	**2275.48**

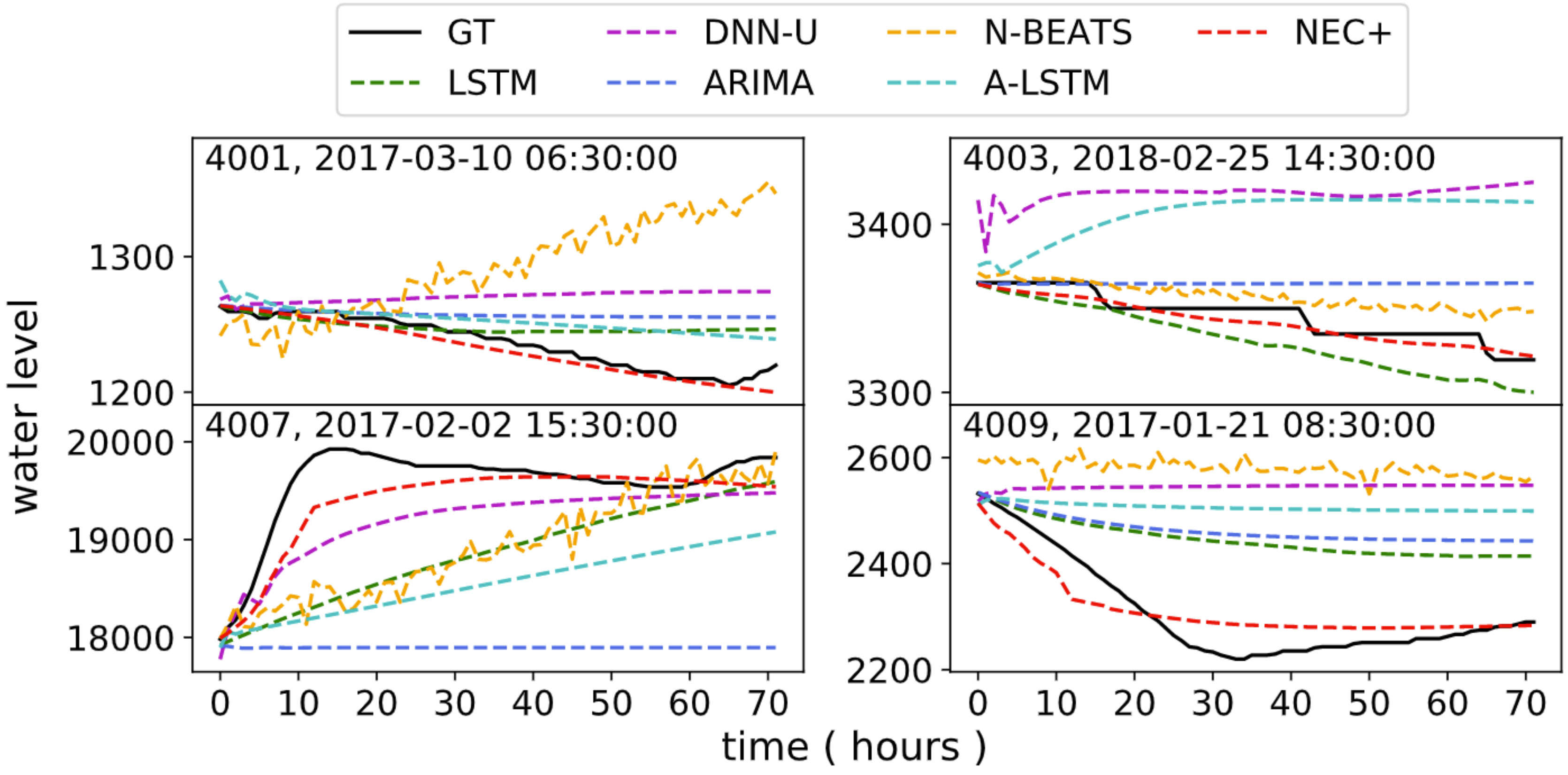
Research Questions:

3. How do the loss function parameters affect performance?



Research Questions:

4. How does NEC+ compare against state-of-the-art baselines?



Evaluation Overall:

Table 1: Effectiveness Comparison (RMSE) of NEC+ Against Baselines for 9 Reservoirs

Model/Reservoir	**4001**	**4003**	**4004**	**4005**	**4006**	**4007**	**4009**	**4010**	**4011**
ARIMA	1016.32	1859.70	2501.97	9692.87	1039.38	5854.48	1060.05	3465.20	690.23
Prophet	8469.74	38827.22	95279.31	181607.50	20904.57	187603.80	28629.44	114115.4	2829.26
LSTM	1167.73	1514.90	2342.71	6730.93	959.05	5035.91	954.04	3734.53	662.48
DNN-U	1162.01	1597.72	3989.20	9878.41	983.27	4320.40	1411.63	4257.58	763.73
A-LSTM	878.71	1536.04	2548.56	8919.33	1638.65	13529.86	1064.15	2914.75	700.50
N-BEATS	937.24	1926.74	2280.83	7153.82	960.42	3153.76	1295.90	3162.17	**514.30**
NEC+	**740.19**	**1411.44**	**1783.92**	**4352.74**	**780.46**	**2092.73**	**703.93**	**2275.48**	632.61

Table 3: MAPE of NEC+ vs. Baselines for 9 Reservoirs

Model/Reservoir	**4001**	**4003**	**4004**	**4005**	**4006**	**4007**	**4009**	**4010**	**4011**
ARIMA	1.3573	0.7626	0.8694	1.2560	1.5401	0.8517	0.9504	1.7871	3.2914
Prophet	16.7877	19.8559	38.9642	35.6662	56.0537	32.9152	31.8069	45.2579	15.3312
LSTM	1.6697	0.6153	0.7450	1.0092	1.3264	0.9253	0.9298	2.5520	3.1282
DNN-U	1.6509	0.6812	1.8738	1.9394	1.4551	0.6509	1.5604	2.1582	3.7131
A-LSTM	1.3533	0.6506	0.8424	1.2060	2.8017	2.1738	0.9705	1.3986	3.4137
N-BEATS	1.3346	0.7972	0.7882	1.1405	2.0061	0.4709	1.4580	1.7146	**2.3108**
NEC+	**1.0319**	**0.5687**	**0.6030**	**0.6350**	**1.0662**	**0.3316**	**0.5992**	**1.2894**	2.9237

Q & A

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