A Dataset Details

A brief summary of the dataset details is provided below.

A.1 Commercial Buildings

A.1.1 EnerNOC:. This dataset contains anonymized energy usage data for 100 commercial/industrial sites in the USA for the entire year of 2012. [1]

A.1.2 I-Blend: This dataset consists of minutely energy usage data from 2013 to 2017 for an academic institution in Delhi, India. The data includes energy consumption from seven campus buildings: Academic, Lecture, Library, Facilities, Dining, Boys' Dormitory, and Girls' Dormitory [9].

A.1.3 DGS:. Washington dataset consists of 15 minute energy consumption data from 322 commercial buildings of Washington for a period of two years. [2]

A.1.4 EWELD:. This dataset [5] includes electricity consumption data of 386 industrial and commercial users in 17 industries, under extreme weather events such as typhoons and extreme heat, which are collected at 15-minute intervals. The data is collected over six years from smart meters installed at the power entry points of users in southern China.

A.2 Residential Buildings

A.2.1 CEEW:. This dataset comprises of electricity consumption of 3-minutes interval from nearly 100 smart meters installed in Mathura and Bareilly districts of Uttar Pradesh, India from May 2019 to October 2021 [1]. It is divided into two datasets, corresponding to individual districts Bareilly and Mathura.

A.2.2 Ireland: This dataset contains smart meter readings from residential households within an energy community in Ireland, as part of StoreNet project [4]. The provided data comprise per household power (W) and energy (Wh) components for active and reactive consumption, PV generation, import, export, charging, discharging and stage of charge of energy storage in 1-minute temporal resolution for the year 2020.

A.2.3 MFRED:. This Multifamily Residential Electricity Dataset (MFRED) contains the electricity use of 390 apartments, ranging from studios to four-bedroom units [6]. All apartments are located in the Northeastern United States, but differ in their heating/cooling system and construction year (early to late 20th century). To adhere to privacy guidelines, data were averaged across 15 apartments each, based on annual electricity use. MFRED includes real and reactive power, at 10-second resolution, for January to December 2019.

A.2.4 NEEA:. The Northwest energy efficiency alliance initiated, The Northwest End Use Load Research (EULR) project as a regional study designed to gather accurate load profiles for electrically-powered equipment in homes and businesses. As closed access, it has provided 15-minutes interval energy consumption from nearly 150 houses participated as part of this project. [3]

A.2.5 NEST:. Next Evolution in Sustainable Building Technologies [2] research platform published the measurement data from three buildings within their platform. These data includes detailed information on energy consumption (electricity, heating, cooling, domestic hot water), building operation (set points, valve openings, windows), and occupant practice (e.g., presence, operation of blinds and kitchen, showering patterns). All data have been measured over four years and with a temporal resolution of 1-minute. In the case of this study, we have considered the residential building UMAR from this platform.

A.2.6 Prayas: This dataset contains 15-minute interval energy data recorded by eMARC meters installed in 115 homes in Maharashtra and Uttar Pradesh. The analysis period spans from January 2018 to June 2020, using data from the main line meters installed in the homes [7].

A.2.7 SMART:* The dataset contains whole-house electricity consumption for 114 single-family apartments for the period of 2016, sampled every 1-minute. [4]

A.2.8 SGSC (Smart Grid Smart City): This dataset, from the SGSC project (2010-2014), links customer time-of-use data (half-hour increments) with demographic information and appliance use data for Australia. It also includes data on climate, product offers, and responses to peak events. The project, funded by the Australian Government and an industry consortium led by Ausgrid, comprises energy consumption data from approximately 13,735 buildings. More details are available on the archived [Department of Industry, Innovation and Science] website [5].

A.2.9 GoiEner: The GoiEner [8] dataset contains 7.2 GB of energy consumption data from smart meters in Spain, covering the period from late 2014 to June 2022. The widespread use of smart meters began in January 2018, reflected in the increasing data volume. The dataset includes data from about 25,559 buildings, with an outlier at the end indicating an incomplete last recorded month.

[1] https://open-enernoc-data.s3.amazonaws.com/anon/index.html
[2] https://github.com/buds-lab/island-of-misfit-buildings.git
[3] https://neea.org/data/nw-end-use-load-research-project/energy-metering-study-data
[4] https://traces.cs.umass.edu/docs/traces/smartstar/
[5] https://data.gov.au/data/dataset/smart-grid-smart-city-customer-trial-data

A.2.10 UK SMART Trials: This dataset is a part of The Energy Demand Research Project (EDRP), which conducted a set of trials, designed to help better understand how domestic consumers react to improved information about their energy consumption over the long term. Energy suppliers carried out trials across Great Britain, incorporating different combinations of measures, and provided closed source data from nearly 14,000 households over a period of around two years. [6].

A.2.11 SAVE:. The Solent Achieving Value from Efficiency (SAVE) project, funded by the Low Carbon Network Fund (LCNF), collected a electricity demand data from 4000 household for the purposes of examining the drivers and practices linked to demand, and to evaluate the impact of a randomised control trial into demand response. The study was conducted in the county of Hampshire, the city of Southampton, the city of Portsmouth and the Isle of Wight. [7].

A.2.12 iFlex: This dataset [3] is a result of field experiment that was conducted to understand if and how households change their power consumption in response to variable hourly electricity prices. This experiment was conducted in several Norwegian regions, and various price signals were tested over two winter periods from early 2020 to spring 2021.

For our study, we used hourly aggregated measurements and wide dataframe (each column represents building name). The dataset utilized in our study is independent and has not been included in any pre-trained models (See Table **??**).

B Model Parameters Details

Table 1: Summary of model parameters and their typical values.

Parameter	Value
Backcast Horizon (context length)	168 (e.g., 7 days)
Forecast Horizon	24 (e.g., 1 day)
Patch Sizes	[8, 12, 24] for base, small, large models
Stride	24 (e.g., 1 day)
Number of Stacks	[3, 4, 6] for base, small, large models
Number of Blocks per Stack	[3, 4] for base, small, large models
Hidden Dimension	128, 256, 512 for base, small, large models
Activation Function	GeLU
Loss Function	Huber
Optimizer	Adam
Learning Rate	1×10^{-4}
Batch Size	1024
Weight Initialization	Xavier Initialization
Dropout Rate	0.2
Epochs	100
Early Stopping	Triggered after 3 epochs

[6]https://doi.org/10.5255/UKDA-SN-7591-1
[7]https://doi.org/10.5255/UKDA-SN-8676-1

C Model Results

C.1 Results on Energy Load Time-Series Test Dataset

Table 2: Comparison of Pre-Training from scratch Models, TFS, and Traditional Models' performance using Median NRMSE for different datasets. (TTMs - Tiny Time Mixers, TFS - Trained From Scratch Transformer, TFT - Temporal Fusion Transformer)

Dataset	Pre-training from scratch			TFS	Traditional ML models		
	NBEATS	TTMs	**MixForecast** (Proposed)	TFT	ARIMA	Linear Regression	LightGBM
Commercial Buildings							
Enernoc	28.60	23.21	22.54	37.92	51.53	28.72	27.13
Iblend	23.00	21.51	19.58	29.49	25.02	26.97	25.97
Average	25.80	<u>22.36</u>	**21.06**	33.71	38.28	27.85	26.55
Residential Buildings							
Mathura	141.72	136.06	132.09	141.60	104.95	101.46	104.76
Bareilly	65.92	64.42	63.28	75.33	78.07	76.68	76.48
MFRED	26.46	24.74	24.39	34.64	42.03	34.15	32.94
NEEA	74.51	69.31	68.52	83.74	92.68	88.07	86.60
NEST	64.95	64.30	64.71	69.64	75.62	68.27	66.18
Prayas	106.85	101.97	100.17	124.09	103.87	81.98	76.25
Smart*	62.75	61.54	61.01	66.42	69.27	93.18	89.10
Ireland	83.45	81.52	81.02	90.11	95.11	95.99	92.29
GoiEner	120.99	117.69	118.27	141.01	119.95	119.20	115.82
SGSC	94.98	92.90	91.47	117.96	111.91	104.22	102.79
Average	84.26	<u>81.45</u>	**80.49**	94.45	89.35	86.32	84.32

Table 3: Comparison of Zero-Shot and Fine-Tuned Models' performance using Median NRMSE for different datasets.

Dataset	Zero-shot				Fine-tuned		
	Moirai	Chronos	Lag-llama	**MixForecast** (Proposed)	Moirai	Lag-llama	**MixForecast** (Proposed)
Commercial Buildings							
Enernoc	29.20	25.99	51.68	22.54	24.68	27.98	20.99
Iblend	27.30	16.17	63.16	19.58	22.00	18.44	19.89
Average	28.25	<u>21.08</u>	57.42	**21.06**	23.34	<u>23.21</u>	**20.44**
Residential Buildings							
Mathura	109.60	102.78	113.49	132.09	91.46	99.34	120.97
Bareilly	69.90	73.84	89.88	63.28	54.41	69.27	58.23
MFRED	27.10	25.39	61.97	24.39	20.80	30.81	24.19
NEEA	80.40	82.64	91.93	68.52	66.81	84.27	70.06
NEST	71.70	71.33	85.00	64.71	54.98	66.90	50.54
Prayas	90.40	87.93	100.47	100.17	56.83	78.03	70.91
Smart*	65.90	69.69	83.61	60.01	65.14	89.12	73.97
Ireland	86.50	92.32	115.63	81.02	70.01	82.84	76.63
GoiEner	111.62	114.59	131.23	118.27	99.34	111.07	96.35
SGSC	92.01	99.43	111.91	91.47	85.24	89.23	82.69
Average	<u>80.51</u>	81.99	98.51	**80.49**	**66.50**	80.09	<u>72.45</u>

C.2 Results on Generic Muitivariate Time-Series Test Dataset

Table 4: Comparison of forecasting performance across different prediction lengths for various models with Multivariate time-series datasets.

Model		**MixForecast**		Informer		Reformer		PatchTSMixer		DLinear	
		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTh1	24	**0.337**	**0.391**	0.722	0.647	0.607	0.573	0.601	0.551	0.601	0.551
	96	**0.517**	**0.516**	0.899	0.725	0.802	0.671	0.779	0.687	0.779	0.687
	192	**0.638**	**0.595**	0.964	0.748	0.934	0.713	0.871	0.73	0.871	0.73
	336	**0.773**	**0.661**	1.138	0.842	0.949	0.74	0.992	0.797	0.992	0.797
	720	**0.855**	**0.724**	1.213	0.88	1.12	0.815	1.101	0.831	1.101	0.831
ETTh2	24	**0.234**	**0.343**	0.679	0.663	0.707	0.683	0.851	0.706	0.851	0.706
	96	**1.486**	**0.912**	3.584	1.518	2.52	1.228	1.759	1.083	1.759	1.083
	192	3.672	1.633	5.264	1.911	**2.524**	**1.266**	4.682	1.738	4.682	1.738
	336	3.55	1.607	5.375	1.937	**2.391**	**1.211**	4.123	1.625	4.123	1.625
	720	3.111	1.496	3.951	1.68	**3.068**	**1.32**	3.173	1.485	3.173	1.485
ETTm1	24	**0.239**	**0.318**	0.33	0.384	0.409	0.447	0.321	0.383	0.321	0.383
	96	**0.415**	**0.433**	0.578	0.537	0.7	0.597	0.639	0.575	0.639	0.575
	192	**0.505**	**0.505**	0.804	0.664	0.892	0.688	0.698	0.629	0.698	0.629
	336	**0.635**	**0.607**	1.108	0.814	1.027	0.737	0.982	0.762	0.982	0.762
	720	**0.755**	**0.662**	1.09	0.804	1.08	0.762	1.063	0.803	1.063	0.803
ETTm2	24	**0.117**	**0.223**	0.204	0.328	0.236	0.344	0.155	0.28	0.155	0.28
	96	**0.21**	**0.319**	0.639	0.633	0.606	0.597	0.525	0.55	0.525	0.55
	192	**0.311**	**0.403**	0.934	0.746	1.463	0.956	0.927	0.73	0.927	0.73
	336	**0.923**	**0.714**	1.703	1.008	1.923	1.041	1.222	0.853	1.222	0.853
	720	4.339	1.542	2.934	1.301	3.019	1.309	**2.788**	**1.217**	2.788	1.217
Electricity	24	**0.126**	**0.236**	0.298	0.394	0.313	0.408	0.235	0.342	0.235	0.342
	96	**0.202**	**0.313**	0.345	0.426	0.293	0.382	0.253	0.353	0.253	0.353
	192	**0.224**	**0.333**	0.362	0.443	0.338	0.414	0.265	0.363	0.265	0.363
	336	**0.252**	**0.352**	0.359	0.44	0.369	0.433	0.279	0.373	0.279	0.373
	720	**0.266**	**0.364**	0.405	0.465	0.317	0.394	0.279	0.369	0.279	0.369
Traffic	24	**0.528**	**0.339**	0.664	0.38	0.676	0.383	0.654	0.376	0.654	0.376
	96	**0.628**	0.394	0.725	0.41	0.691	0.381	0.659	**0.358**	0.659	0.358
	192	**0.618**	0.405	0.713	0.399	0.687	0.373	0.657	**0.358**	0.657	0.358
	336	0.651	0.407	0.862	0.482	0.686	0.371	**0.647**	**0.349**	0.647	0.349
	720	0.715	0.44	1.01	0.558	**0.687**	0.37	0.69	**0.366**	0.69	0.366
Weather	24	**0.093**	**0.139**	0.203	0.279	0.182	0.255	0.168	0.241	0.168	0.241
	96	**0.167**	**0.236**	0.376	0.435	0.288	0.348	0.335	0.387	0.335	0.387
	192	**0.218**	**0.288**	0.427	0.441	0.415	0.447	0.545	0.508	0.545	0.508
	336	**0.313**	**0.355**	0.549	0.519	0.76	0.654	0.714	0.599	0.714	0.599
	720	**0.468**	**0.438**	0.944	0.72	0.883	0.702	0.849	0.67	0.849	0.67
Exchange	24	**0.052**	**0.17**	0.589	0.606	0.557	0.596	0.298	0.434	0.298	0.434
	96	**0.193**	**0.331**	0.893	0.759	1.171	0.868	0.761	0.664	0.761	0.664
	192	**0.962**	**0.738**	1.216	0.869	1.374	0.955	1.0	0.753	1.0	0.753
	336	**1.339**	**0.886**	1.575	1.008	1.851	1.104	1.498	0.945	1.498	0.945
	720	**1.611**	**0.993**	2.656	1.339	1.959	1.177	2.58	1.309	2.58	1.309
Illness	24	4.333	1.463	5.175	1.558	**3.771**	**1.257**	4.426	1.398	4.426	1.398
	36	4.456	1.504	5.446	1.637	**3.897**	**1.287**	4.617	1.434	4.617	1.434
	48	4.72	1.521	5.192	1.574	**4.138**	**1.338**	4.729	1.446	4.729	1.446
	60	4.926	1.579	5.311	1.586	**4.326**	**1.374**	5.156	1.525	5.156	1.525

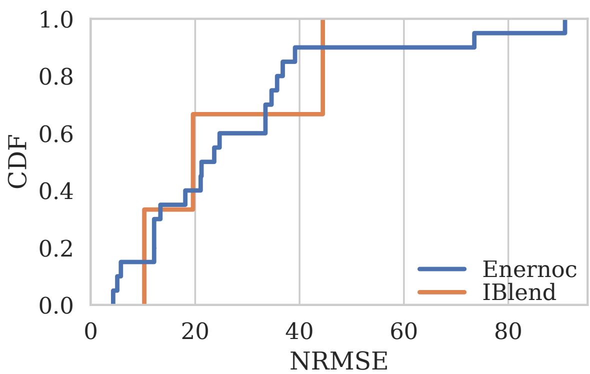
C.3 Results on Generic Univariate Time-Series Test Dataset

Table 5: Comparison of forecasting performance across different prediction lengths for various models with Univariate time-series datasets.

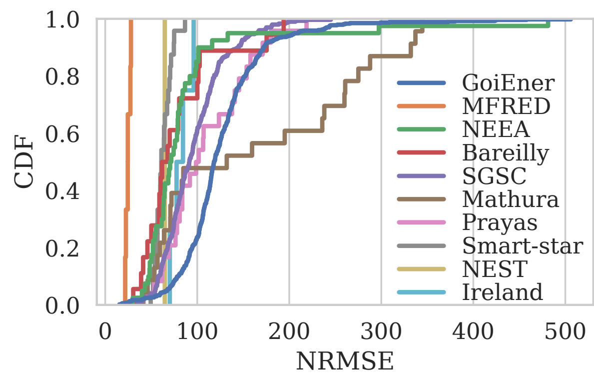
Dataset	PL	MixForecast		Informer		Reformer		LogTrans		NBEATS	
		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTh1	24	**0.061**	**0.191**	0.098	0.262	0.17	0.345	0.087	0.24	0.107	0.274
	96	**0.139**	0.3	0.303	0.478	0.568	0.688	0.315	0.495	0.14	**0.294**
	192	**0.158**	**0.321**	0.394	0.555	0.497	0.64	0.336	0.509	0.238	0.411
	336	**0.158**	**0.317**	0.3	0.481	0.35	0.508	0.708	0.782	0.166	0.329
	720	0.308	0.481	0.318	0.498	0.523	0.663	0.567	0.698	**0.274**	**0.451**
ETTh2	24	**0.086**	**0.223**	0.139	0.294	0.119	0.275	0.088	0.229	0.095	0.236
	96	**0.176**	**0.334**	0.314	0.459	0.197	0.367	0.207	0.371	0.235	0.381
	192	0.223	0.372	0.279	0.426	**0.198**	**0.369**	0.22	0.385	0.325	0.458
	336	0.22	**0.369**	0.28	0.427	**0.204**	0.376	0.254	0.409	0.258	0.403
	720	0.225	0.384	0.263	0.417	**0.19**	**0.364**	0.227	0.395	0.33	0.47
ETTm1	24	0.02	0.106	0.029	0.137	0.023	0.116	0.019	0.105	**0.016**	**0.096**
	96	**0.082**	0.236	0.139	0.3	0.159	0.324	0.082	**0.228**	0.105	0.272
	192	0.127	0.287	0.262	0.443	0.202	0.369	0.197	0.359	**0.103**	**0.259**
	336	0.28	0.44	0.362	0.541	**0.178**	**0.336**	0.304	0.452	0.197	0.362
	720	0.389	0.542	0.391	0.543	0.341	0.509	0.419	0.575	**0.329**	**0.499**
ETTm2	24	**0.019**	**0.094**	0.041	0.156	0.042	0.149	0.019	0.095	0.028	0.117
	96	**0.07**	**0.195**	0.083	0.22	0.091	0.234	0.072	0.204	0.072	0.198
	192	**0.105**	**0.247**	0.122	0.27	0.157	0.321	0.172	0.33	0.112	0.251
	336	0.186	0.338	0.177	0.325	0.205	0.376	0.21	0.361	**0.16**	**0.313**
	720	0.329	0.46	0.231	0.381	0.192	0.366	**0.17**	**0.329**	0.3	0.432
Electricity	24	0.195	0.32	0.193	0.324	0.252	0.371	**0.191**	**0.319**	0.231	0.34
	96	0.284	0.377	**0.262**	**0.366**	0.3	0.401	0.309	0.401	0.331	0.403
	192	0.324	0.401	**0.277**	**0.377**	0.315	0.412	0.377	0.45	0.342	0.415
	336	0.369	0.442	**0.321**	**0.416**	0.375	0.453	0.426	0.481	0.398	0.449
	720	0.427	0.478	0.716	0.659	**0.355**	**0.445**	0.441	0.495	0.451	0.488
Traffic	24	**0.142**	**0.229**	0.179	0.281	0.235	0.32	0.152	0.241	0.149	0.238
	96	**0.172**	**0.263**	0.255	0.347	0.359	0.406	0.248	0.339	0.184	0.273
	192	**0.174**	**0.265**	0.278	0.362	0.417	0.45	0.258	0.351	0.185	0.276
	336	**0.176**	**0.271**	0.295	0.377	0.449	0.467	0.295	0.375	0.191	0.287
	720	0.232	0.325	0.339	0.412	0.462	0.479	0.457	0.507	**0.197**	**0.297**
Weather	24	**0.002**	**0.032**	0.003	0.042	0.003	0.038	0.002	0.034	0.231	0.34
	96	**0.002**	**0.034**	0.003	0.042	0.006	0.063	0.013	0.101	0.331	0.403
	192	**0.003**	**0.039**	0.005	0.058	0.183	0.057	0.005	0.058	0.342	0.415
	336	**0.003**	**0.039**	0.004	0.046	0.012	0.09	0.011	0.087	0.398	0.449
	720	**0.003**	**0.039**	0.015	0.08	0.013	0.093	0.018	0.112	0.451	0.488
Exchange	24	0.051	0.177	0.069	0.213	0.259	0.394	0.048	0.172	**0.04**	**0.157**
	96	**0.194**	**0.343**	0.431	0.498	0.529	0.577	0.431	0.488	0.407	0.477
	192	1.29	0.819	**1.034**	0.82	1.125	0.872	1.326	**0.808**	1.387	0.971
	336	1.872	1.095	**1.209**	**0.852**	1.712	1.098	1.498	0.92	2.11	1.117
	720	2.559	1.288	**1.174**	**0.882**	3.006	1.544	2.504	1.274	2.695	1.268
Illness	24	**1.917**	**1.149**	6.037	2.209	3.563	1.668	3.618	1.649	2.213	1.259
	36	**1.876**	1.203	5.551	2.125	3.915	1.782	4.051	1.781	1.888	**1.181**
	48	**1.966**	**1.236**	5.11	2.04	3.824	1.771	4.073	1.804	2.176	1.308
	60	**2.416**	**1.383**	5.491	2.112	4.058	1.827	4.33	1.876	3.449	1.673

D Error Analysis

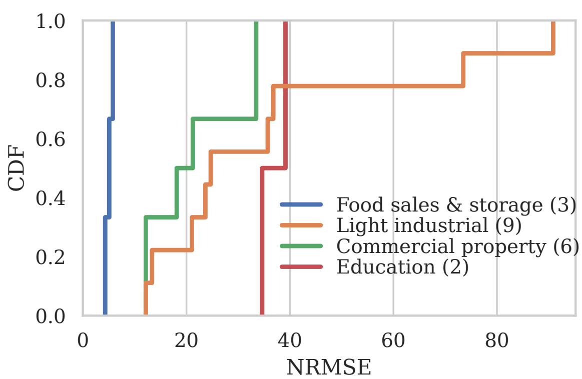
D.1 Cumulative distribution plots of NRMSE of MixForecast



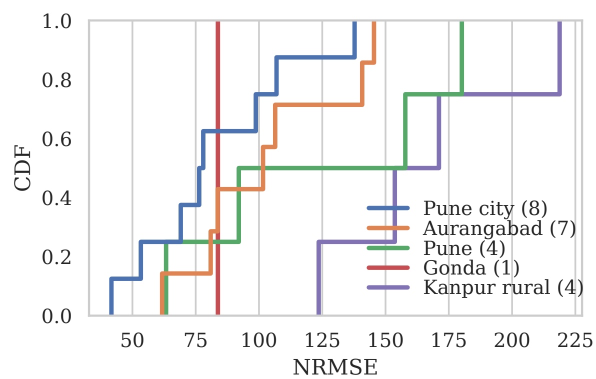
(a) Commercial Buildings.



(b) Residential Buildings.



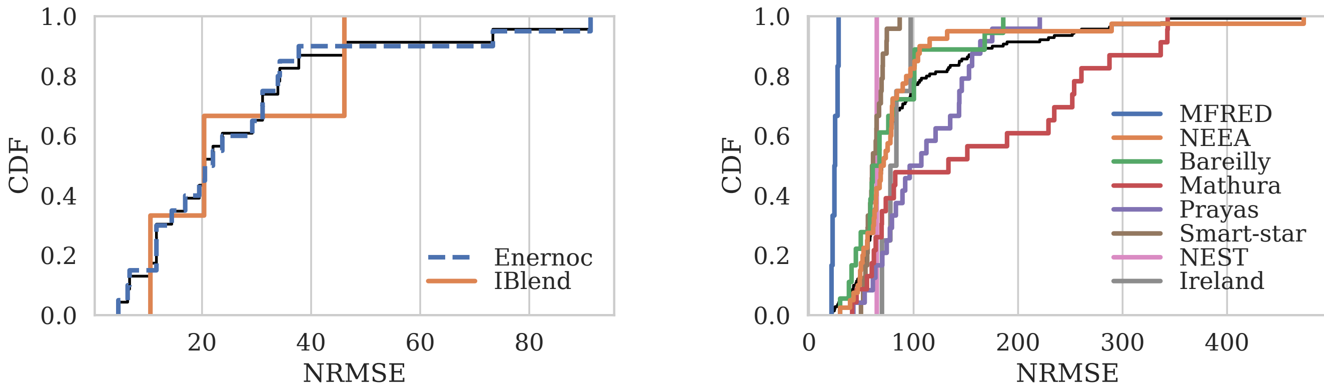
(c) Building types in Enernoc dataset.



(d) Building regions in Prayas dataset.

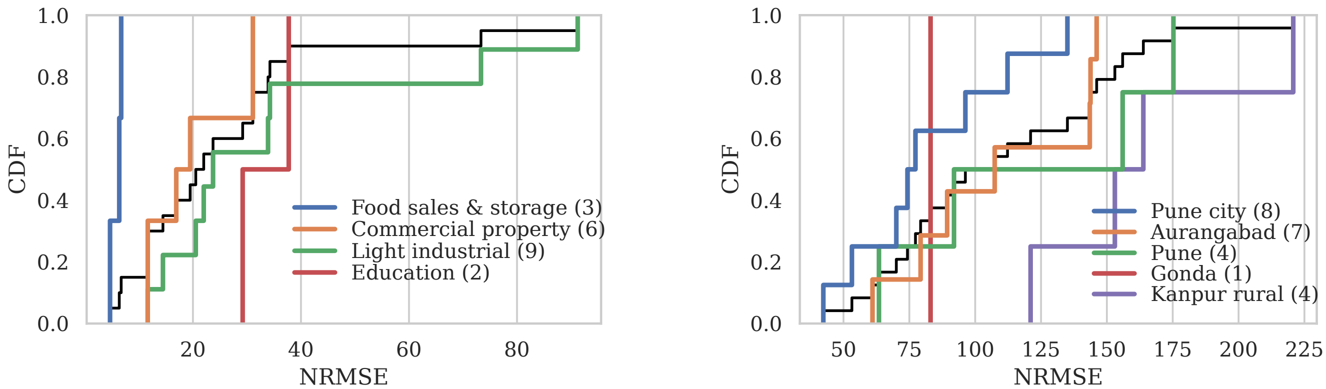
Figure 1: Cumulative distribution plots of NRMSE of MixForecast for different building categories (a) commercial, (b) residential, (c) building types of Enernoc dataset and (d) building regions of Prayas dataset.

D.2 Cumulative distribution plots of NRMSE of zero-shot TTMs



(a) Commercial Buildings.

(b) Residential Buildings.

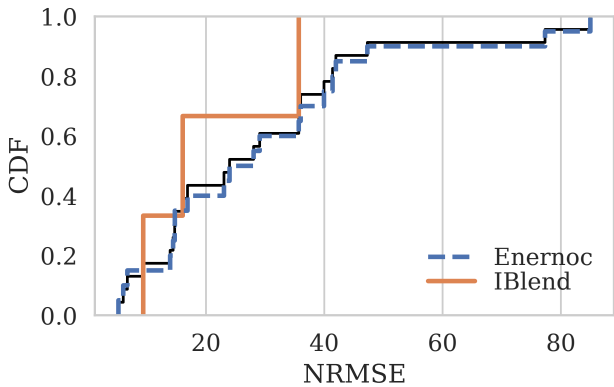


(c) Building types in Enernoc dataset.

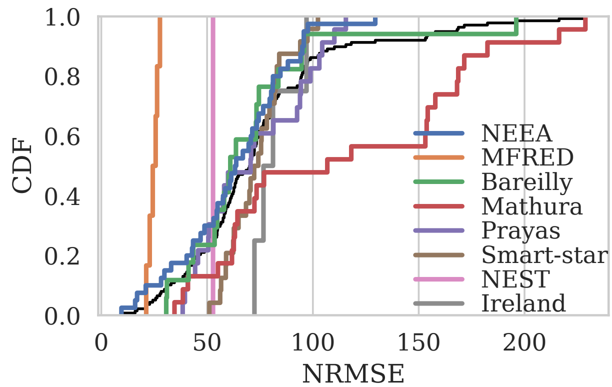
(d) Building regions in Prayas dataset.

Figure 2: Cumulative distribution plots of NRMSE of Zero-shot of TTMs for different building categories (a) commercial, (b) residential, (c) building types of Enernoc dataset and (d) building regions of Prayas dataset. Black line in CDF plots 2a, 2b indicate the average of datasets of respective buildings and 2c and 2d indicates the average of all building types of Enernoc dataset and all building regions of Prayas dataset)

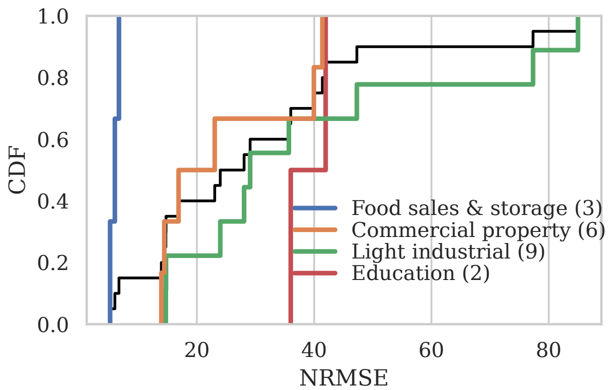
D.3 Cumulative distribution plots of NRMSE of fine-tuned TTMs



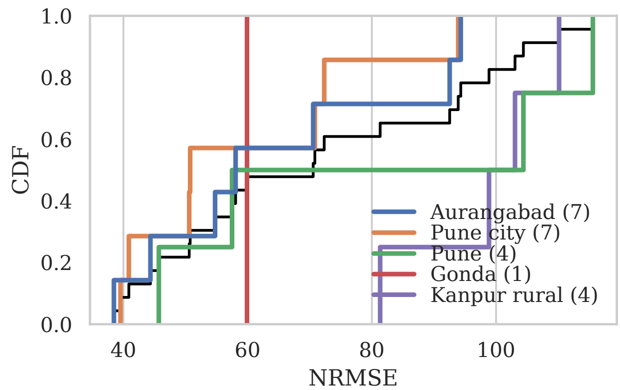
(a) Commercial Buildings.



(b) Residential Buildings.



(c) Building types in Enernoc dataset.



(d) Building regions in Prayas dataset.

Figure 3: Cumulative distribution plots of NRMSE of Fine-tuned TTMs for different building categories (a) commercial, (b) residential, (c) building types of Enernoc dataset and (d) building regions of Prayas dataset. Black line in CDF plots 3a, 3b indicate the average of datasets of respective buildings and 3c and 3d indicates the average of all building types of Enernoc dataset and all building regions of Prayas dataset)

E Prediction Time-series Plots

E.1 Prediction Time-series Plots for Enernoc Buildings

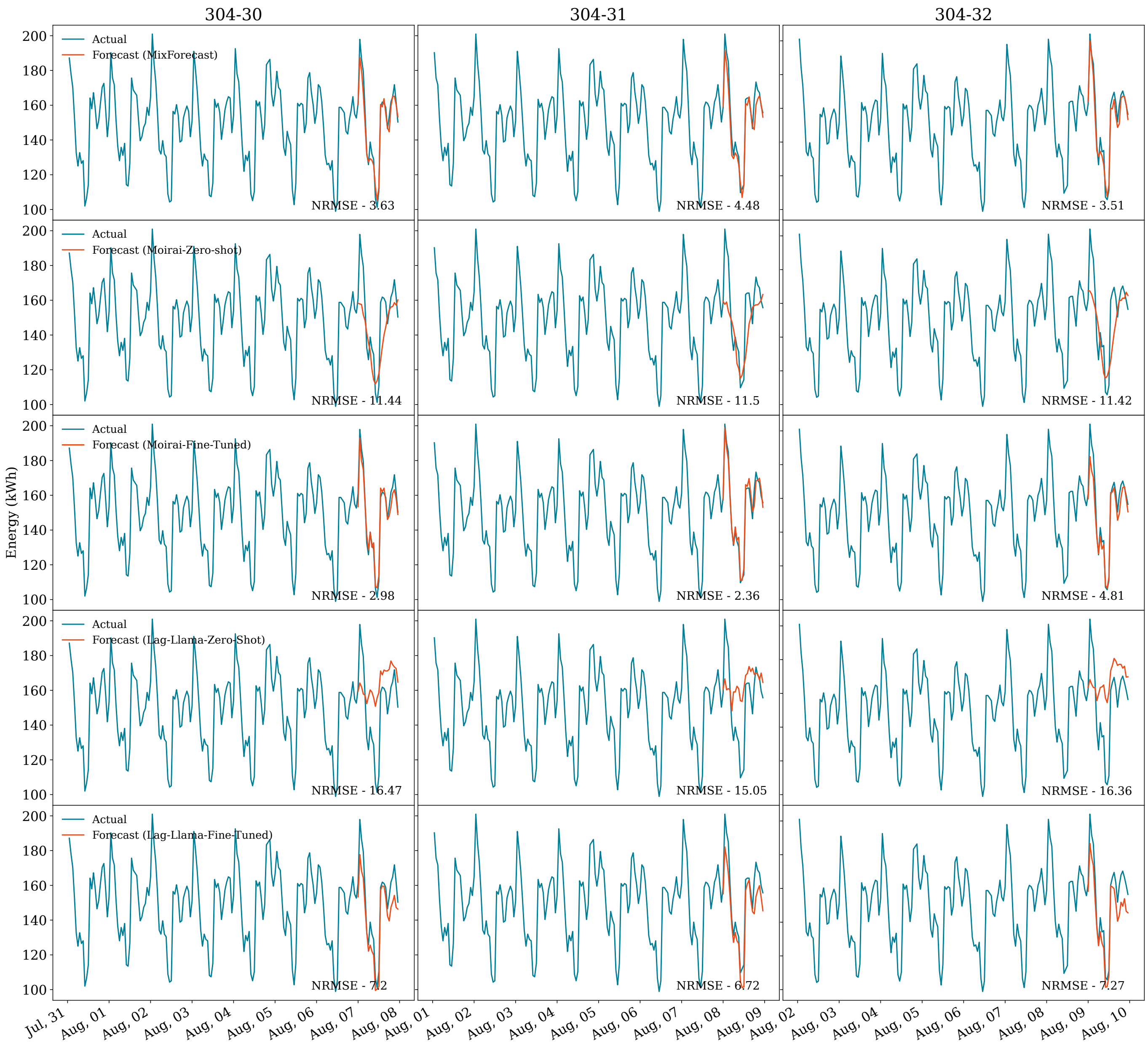


Figure 4: Comparison of forecasting accuracy of subsequent windows for building '304' between MixForecast, Zero-shot and Fine-tuned Moirai, Lag-Llama and TimesFM models from Enernoc commercial dataset with NRMSE value for the each window. (Building Name-Window number)

E.2 Prediction Time-series Plots for Bareilly Buildings

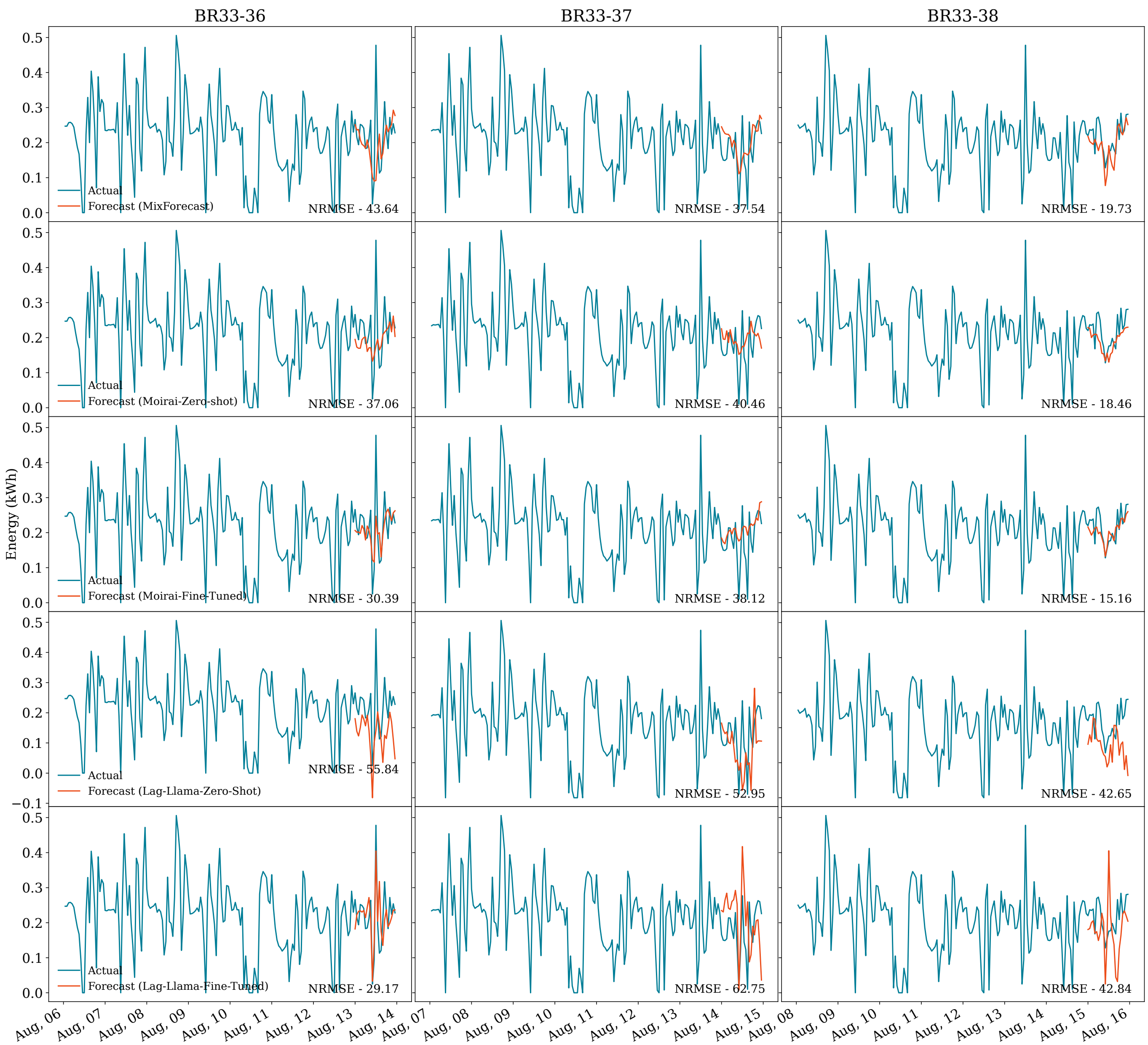


Figure 5: Comparison of forecasting accuracy of subsequent windows for building 'BR33' between MixForecast, Zero-shot and Fine-tuned Moirai, Lag-Llama and TimesFM models from CEEW residential dataset with NRMSE value for the each window. (Building Name-Window number)

F Additional Information

F.1 Activation Function

The GELU activation is defined as:

$$\mathrm{GELU}(x) = 0.5\,x\left(1 + \tanh\left(\sqrt{\frac{2}{\pi}}\left(x + 0.044715x^3\right)\right)\right)$$

F.2 Loss Function

Pre-training time series foundation models at a large scale presents significant challenges in training stability due to the massive datasets and the vast number of parameters involved. To address this, we use the Huber loss, which provides greater robustness to outliers and improves training stability. Specifically, we adopt the Smooth L1 loss by setting $\delta = 1$:

$$\mathcal{L}(x_t, \hat{x}_t) = \begin{cases} \frac{1}{2}(x_t - \hat{x}_t)^2, & \text{if } |x_t - \hat{x}_t| \le \delta, \\ \delta \times (|x_t - \hat{x}_t| - \frac{1}{2} \times \delta), & \text{otherwise.} \end{cases} \tag{1}$$

Here, $\delta = 1$ ensures a smooth transition between the L1 and L2 loss components, mitigating the impact of large outliers while maintaining sensitivity to smaller errors.

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