

SUSTAINABILITY AND RESILIENCE: HOW TO OPTIMIZE PV CHARGING STATIONS'S OPERATION UNDER UNCERTAINTY

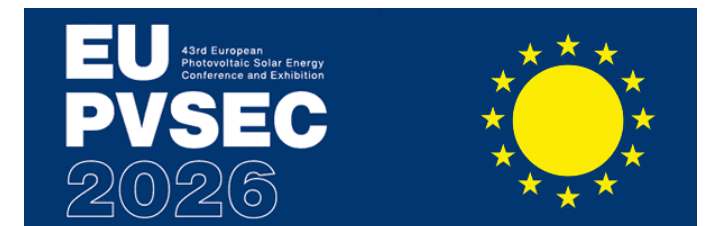
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Assistant Professor
Faculty of Engineering Technology
University of Twente



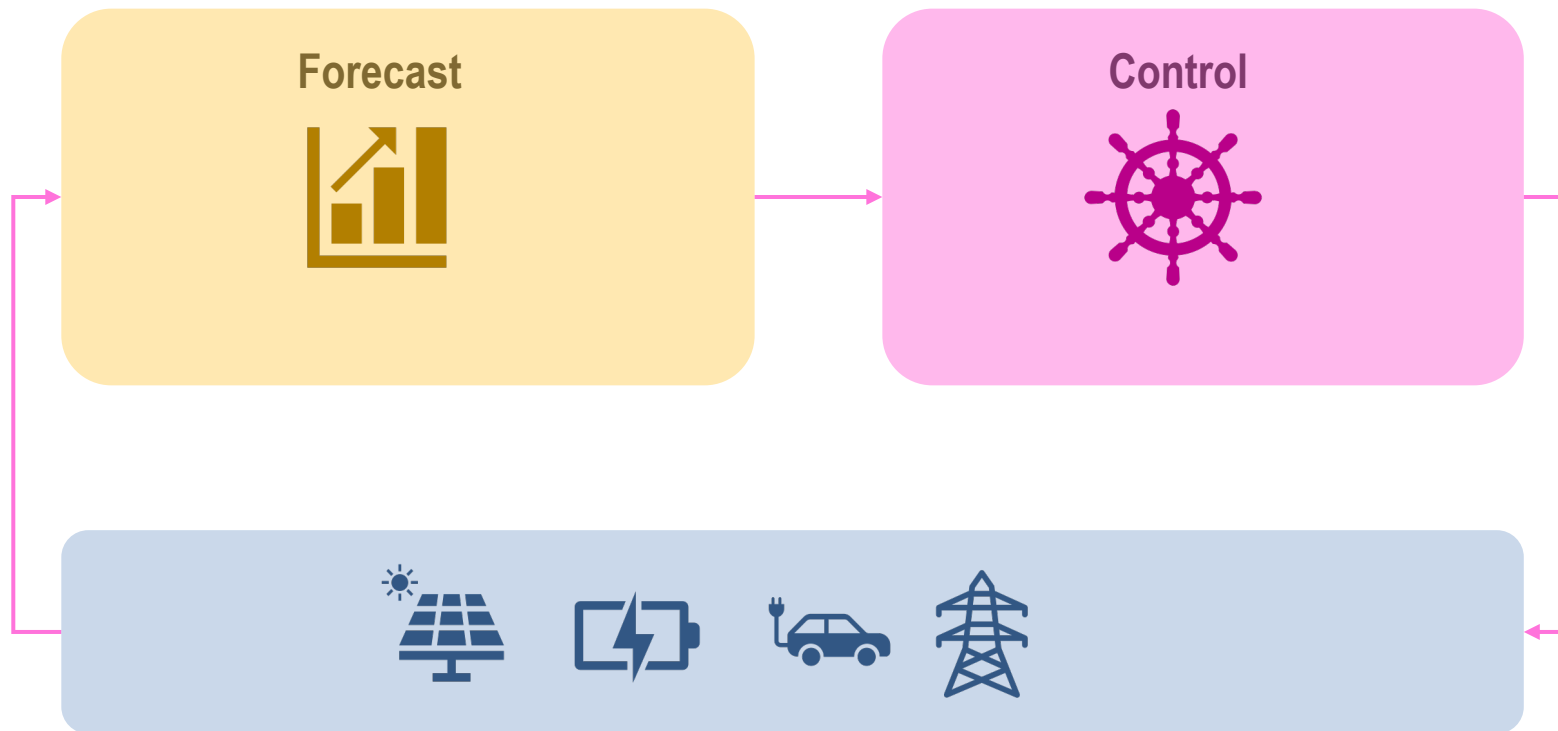
UNIVERSITY OF TWENTE.

| SOLAR CENTRE

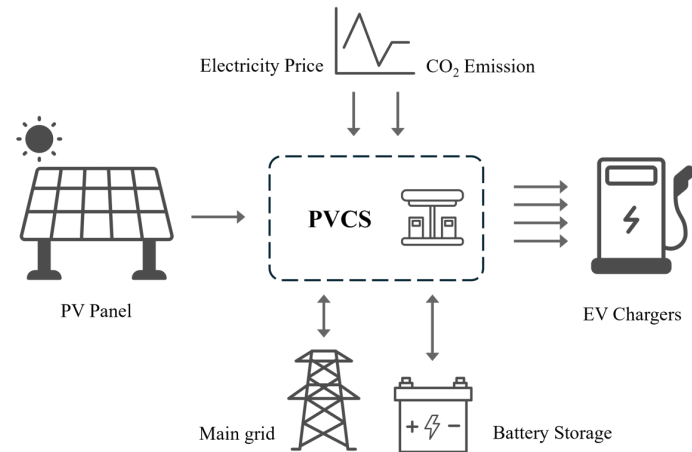


HOW TO MANAGE UNCERTAINTY?

1. identifying the sources of unknowns and quantifying their effects (forecast)
2. building flexible strategies or robust models (control)



LIVING LAB 1: SOLAR CHARGING STATION – UNIVERSITY OF TWENTE

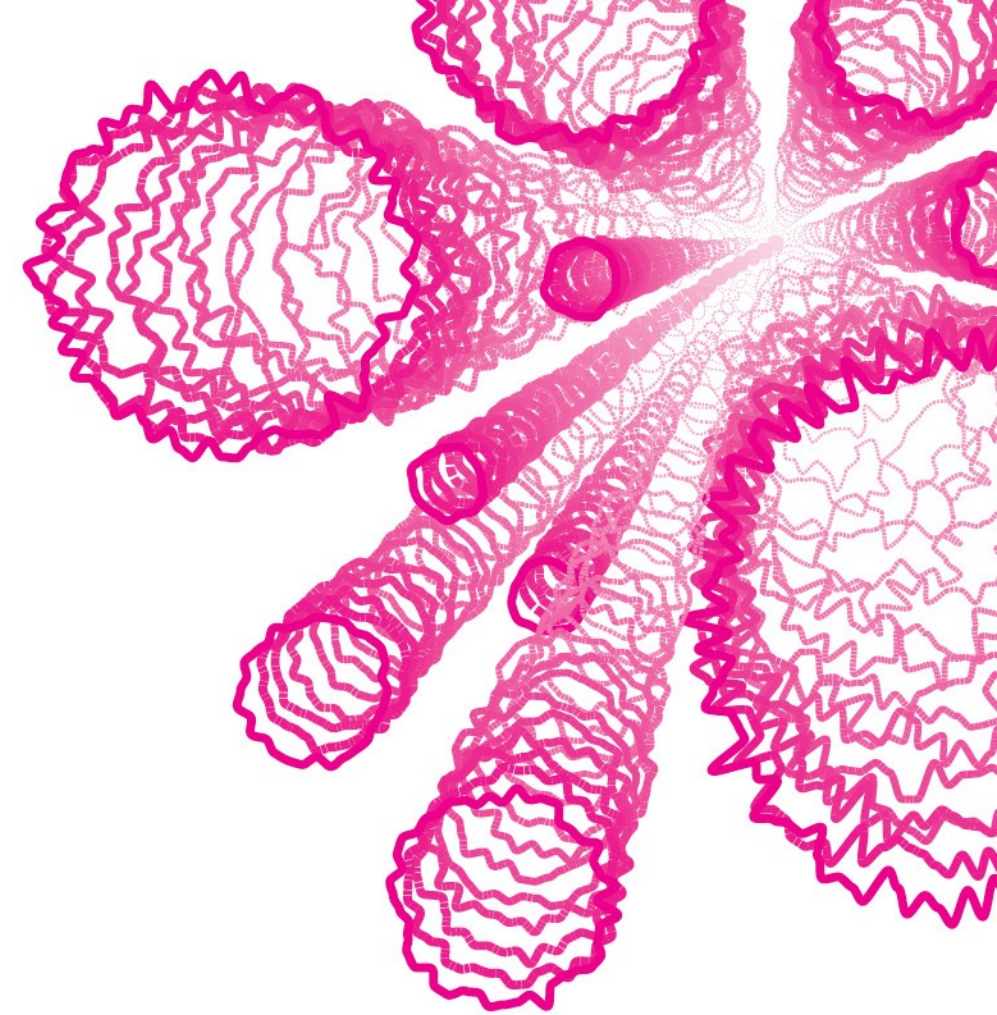


Parameter	Value
Battery storage capacity	30 kWh
Storage charging/discharging max rate	14 kW
Max charging rate for each charging station	11 kW
Grid power exchange max rate	86 kW
Rated power of PV panel	360 W _p
PV inverter max power rate	25 kW

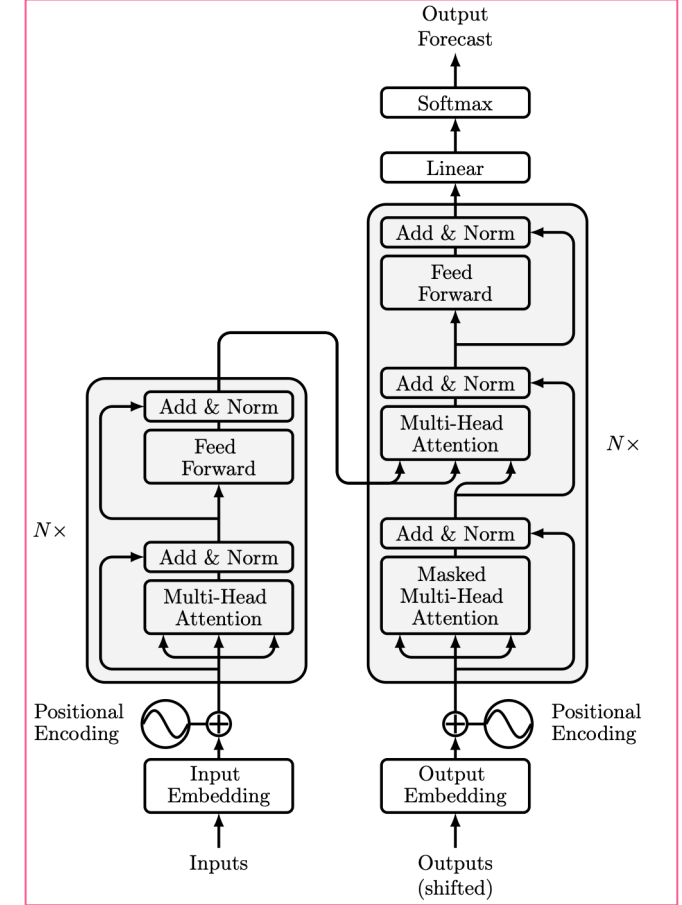
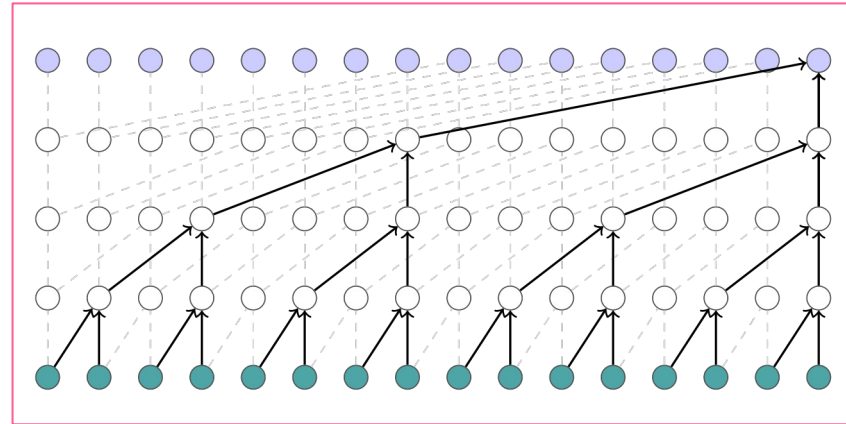
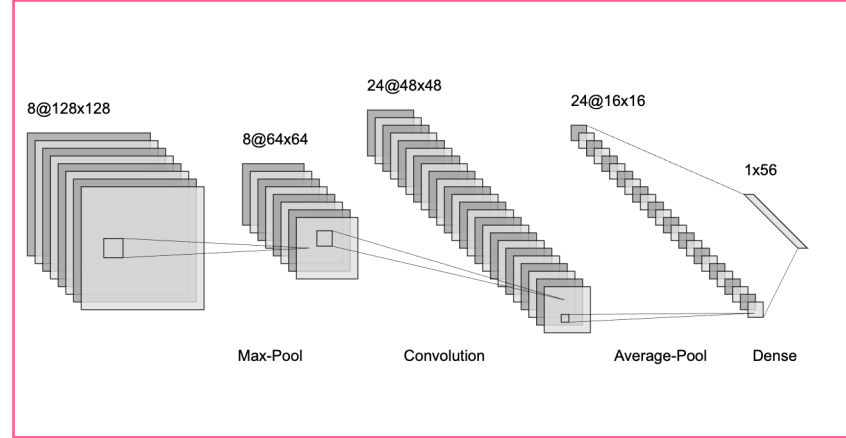
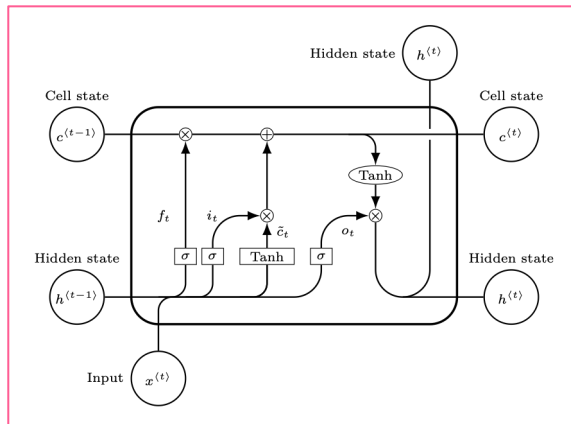
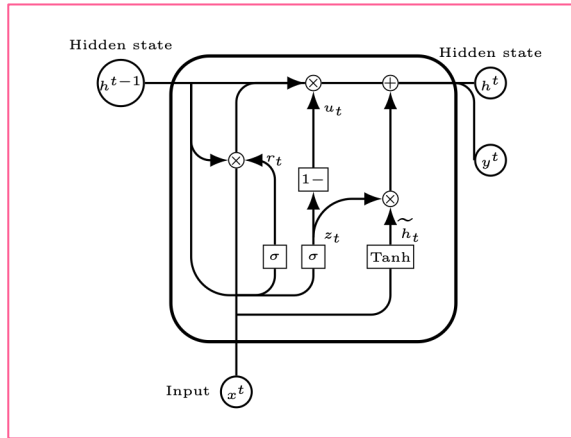
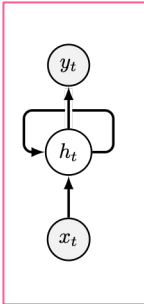


WHAT IF WE USE MEMORY IN FORECASTING?

- SEQUENTIAL DEEP LEARNING ARCHITECTURES
FOR PV FORECASTING

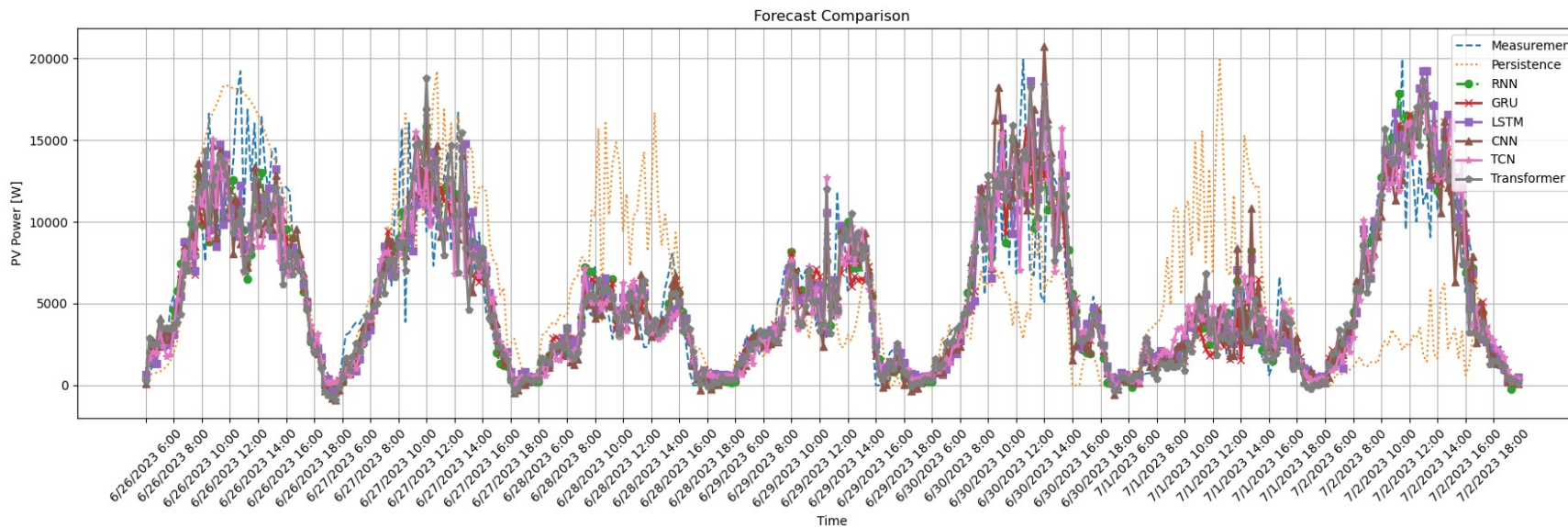


SEQUENTIAL DEEP LEARNING ARCHITECTURES FOR PV FORECASTING



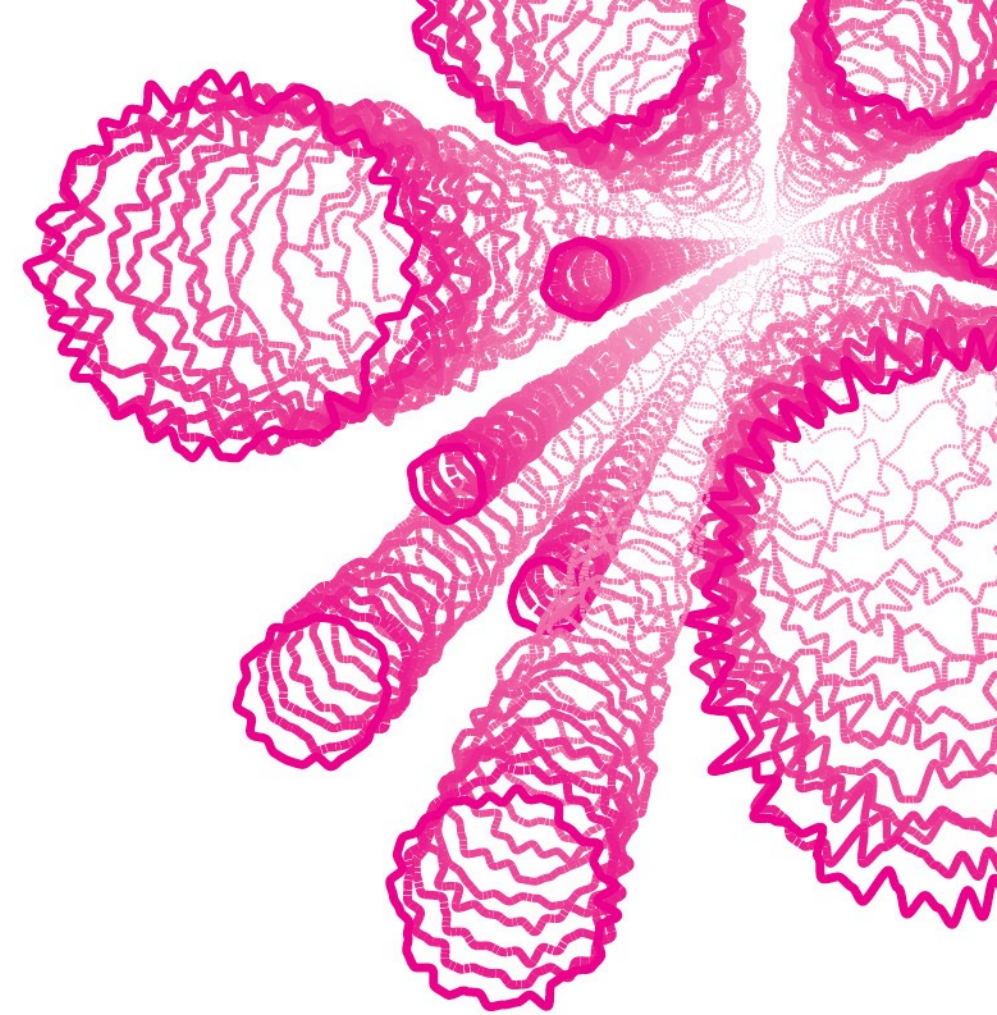
SEQUENTIAL DEEP LEARNING ARCHITECTURES FOR PV FORECASTING

Model	Architecture	Unit	Kernel size	Dropout	Optimizer	Activation	Learning rate
RNN	Vanilla RNN + D	64,64		0.3	ADAM	ReLU	0.001
GRU	GRU+D	64,64		0.3	ADAM	ReLU	0.001
LSTM	2LSTM+D	64,64		0.3	ADAM	ReLU	0.001
CNN	2Conv 1D+Max Pool + D	64,128,64	3	0.3	ADAM	ReLU	0.001
TCN	Causal Conv 1D + Dilated Causal Conv 1D + D	64,64,64	3	0.3	ADAM	ReLU	0.001
Transformer	MHA + FFN + D	2,56,64		0.3	ADAM	ReLU	0.001

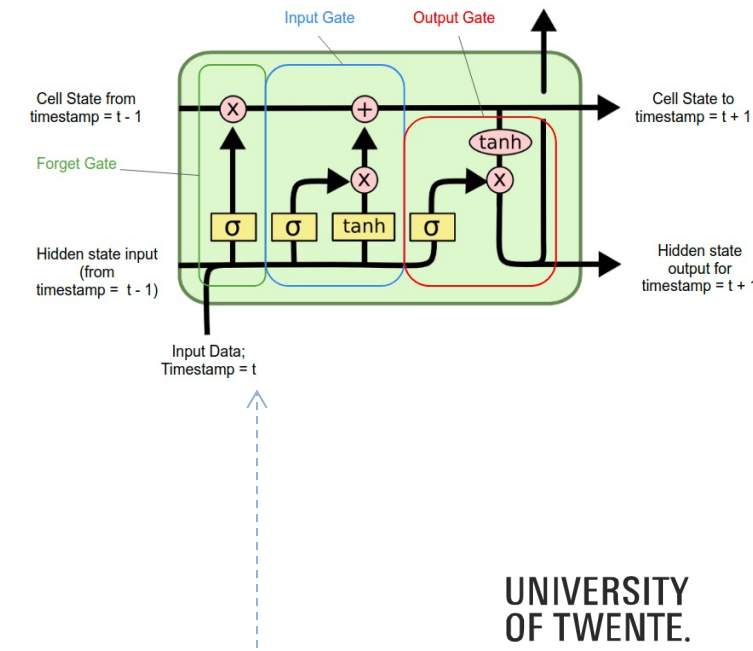
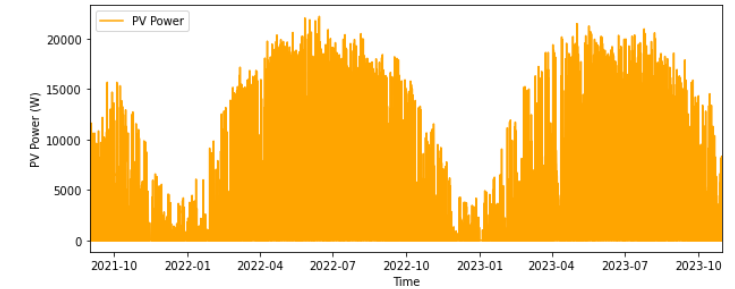
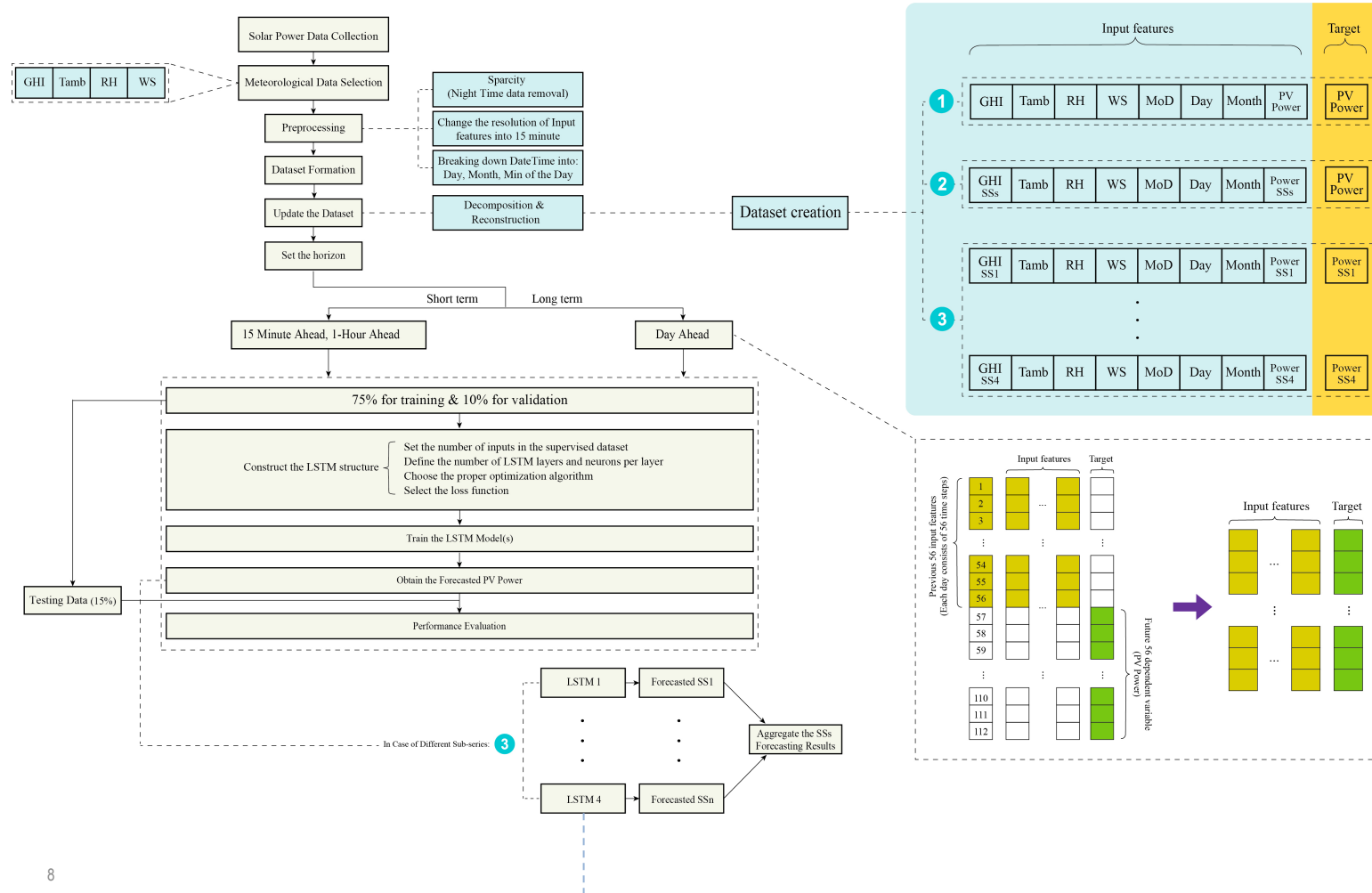


LET'S ZOOM INTO ONE OF THE MOST ACCURATE MODELS

- USE LONG-SHORT TERM MEMORY FOR PV FORECAST

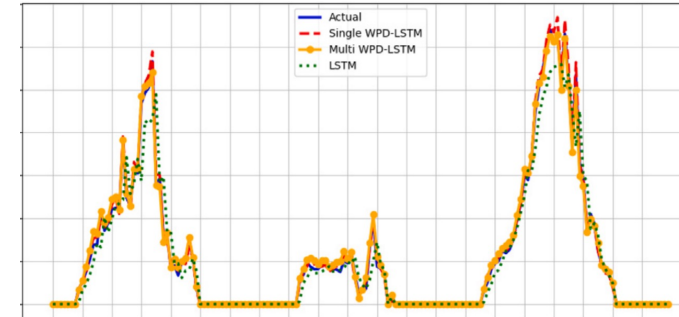


MULTI-TEMPORAL PV POWER PREDICTION USING LSTM AND WPD

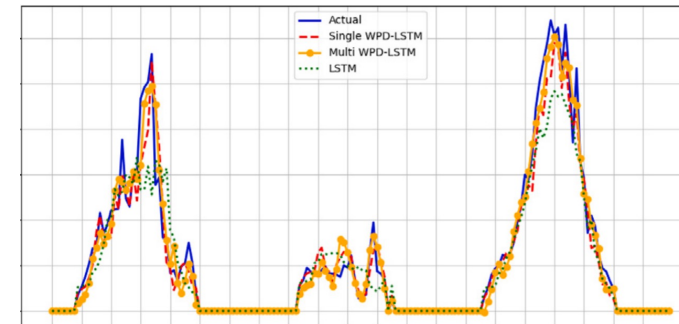


STUDY 1) MULTI-TEMPORAL PV POWER PREDICTION USING LSTM AND WPD

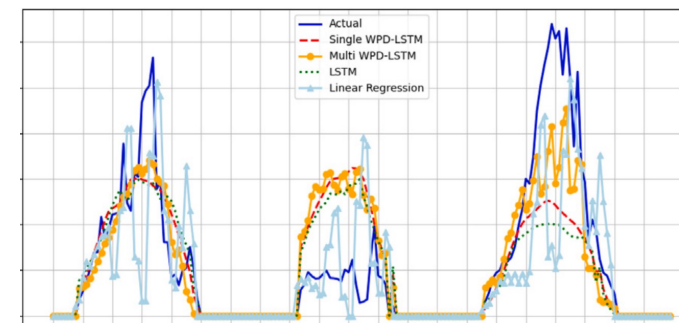
- Hybrid WPD-LSTM: combines signal decomposition with LSTM for improved PV forecasting.
- Multi-temporal forecasting: evaluated for 15-min, 1-hour, and day-ahead horizons.
- Signal decomposition: separating long-term trends from short-term fluctuations.
- Best performance: achieved nRMSE of 2.67%, 7.31%, and 12.93% across the three horizons.



15 minutes ahead



1 hour ahead

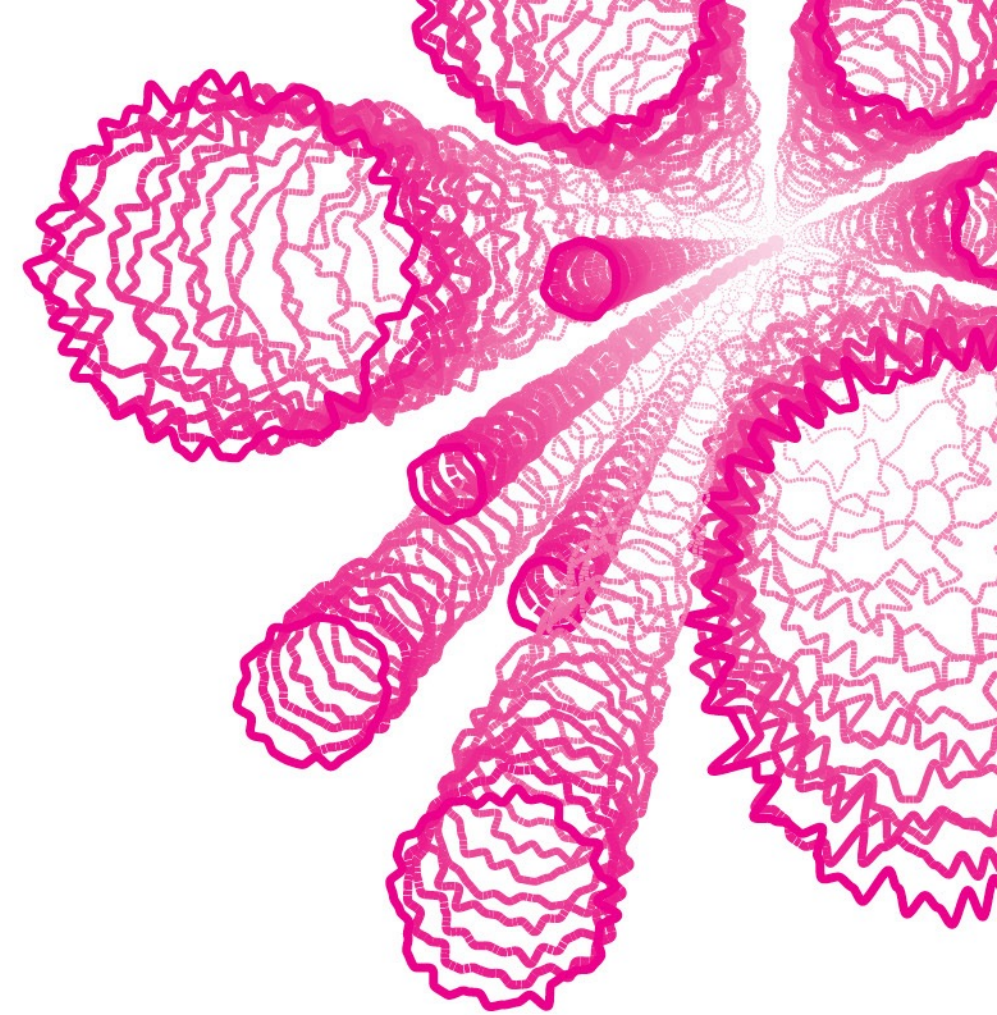


day ahead

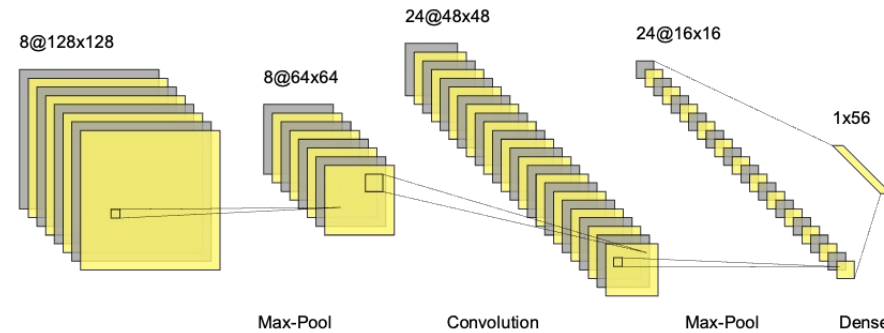
Sardarabadi, A., Ardakani, A. H., Matrone, S., Ogliari, E., & Shirazi, E. (2025). Multi-temporal PV power prediction using long short-term memory and wavelet packet decomposition. *Energy and AI*, 21, 100540.

LET'S ZOOM INTO ONE OF THE LEAST ACCURATE MODELS

- AND IMPROVE IT



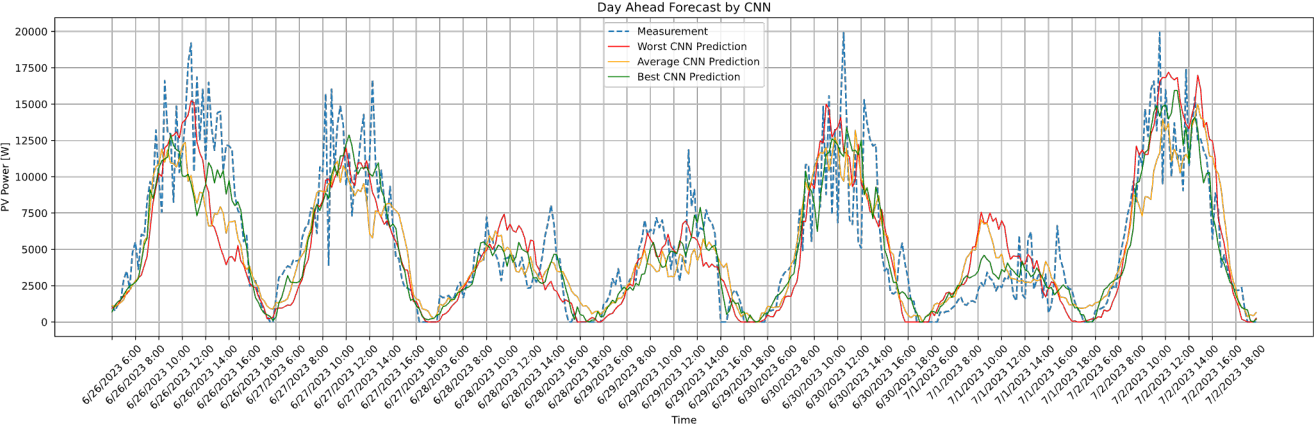
CNN HYPERPARAMETER TUNING FOR IMPROVING PV FORECAST



Number of filters	Kernel size	Pool size	Dense unit	Dropout rate	Learning rate	Activation
32, 64, 128	3, 5, 7	2, 3	32, 64	0.2, 0.3	0.001, 0.0005	Tanh, Relu

Shirazi, E. & Ardakani, A. H. (2025, October). Enhancing Convolutional Neural Network Performance for Forecasting in Energy Systems via Hyperparameter Tuning. In *2025 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT Europe)* (pp. 1-5). IEEE.

STUDY 4) CNN HYPERPARAMETER TUNING FOR PV FORECAST

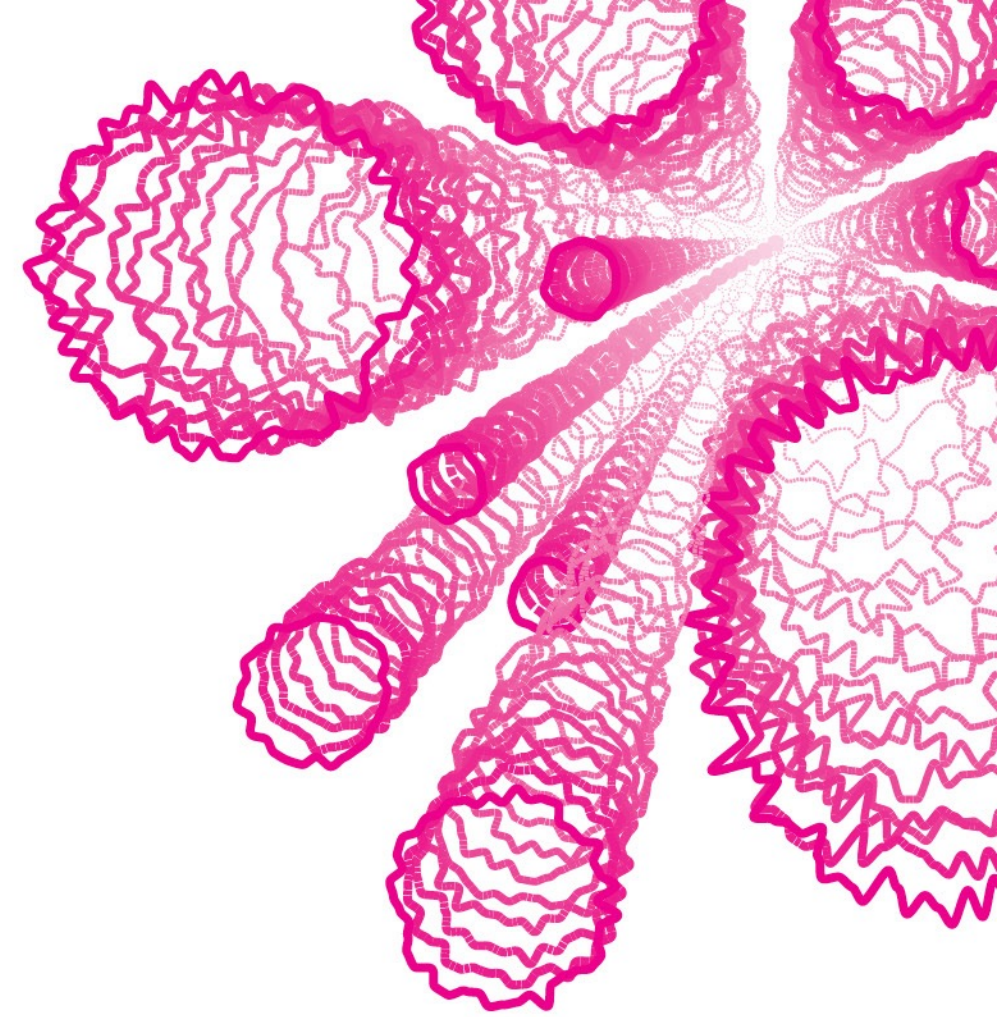


Model	nRMSE
Persistence (benchmark)	20.01 %
Best-performing CNN	9.97 %
Average-performing CNN	12.31 %
Worst-performing CNN	15.29 %

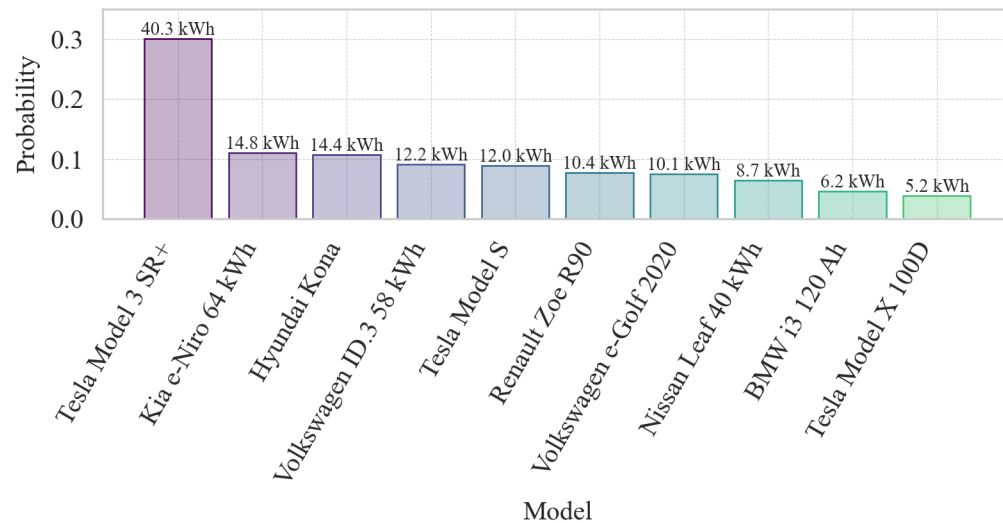
Model	Number of filters	Kernel size	Pool size	Dense unit	Dropout	Learning rate	Activation
Best CNN	32	5	2	32	0.3	0.0005	Tanh
Average CNN	128	5	3	32	0.3	0.0005	Tanh
Worst CNN	64	7	3	64	0.3	0.001	Tanh

HOW TO CONTROL THE CHARGING SESSION?

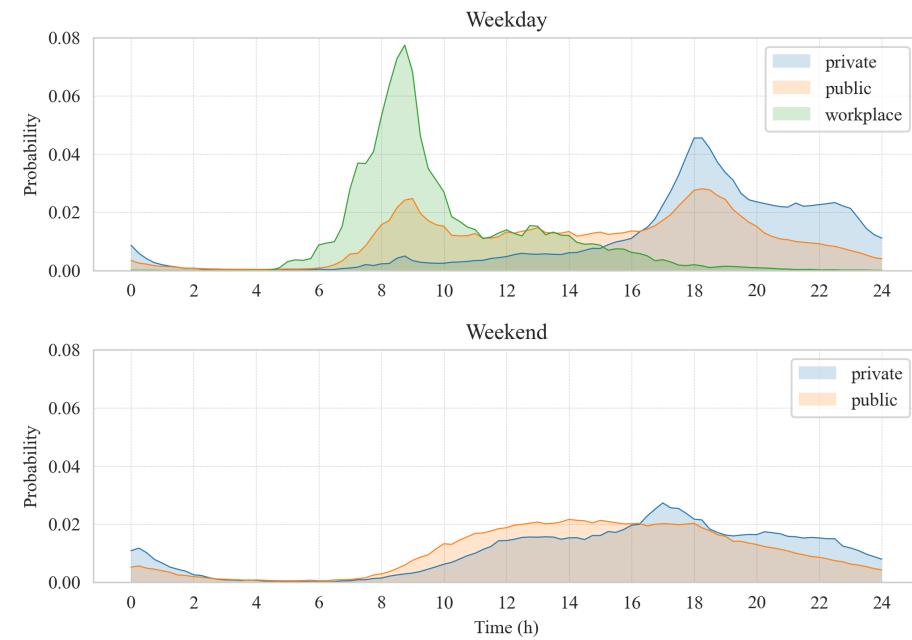
- BUILD FLEXIBLE STRATEGIES TO MANAGE UNCERTAINTY



CHARGING BEHAVIOR AND EV TYPES

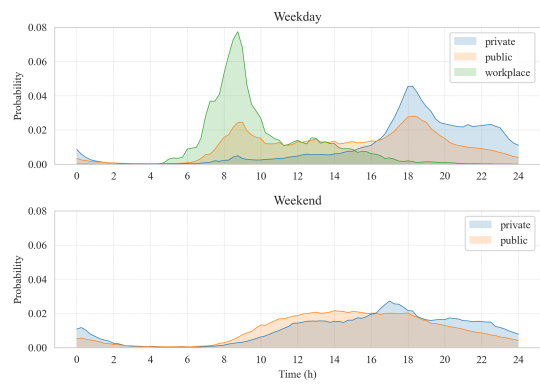
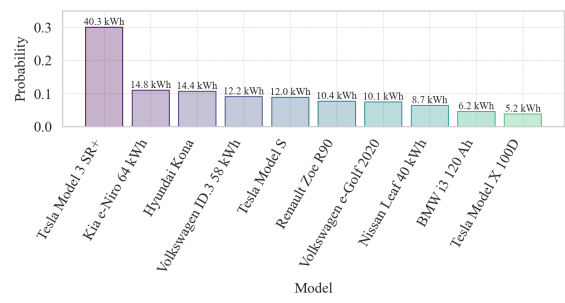


EV types

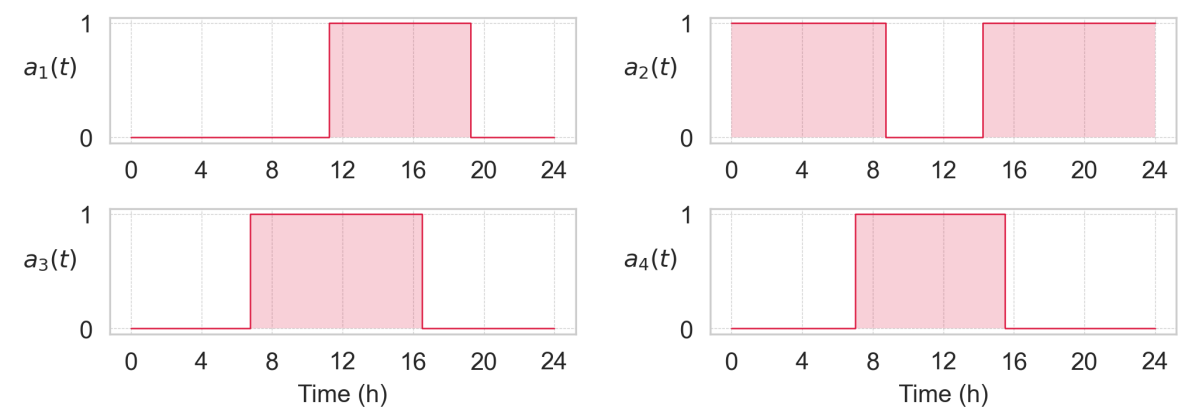


EV arrival distribution

EV AVAILABILITIES



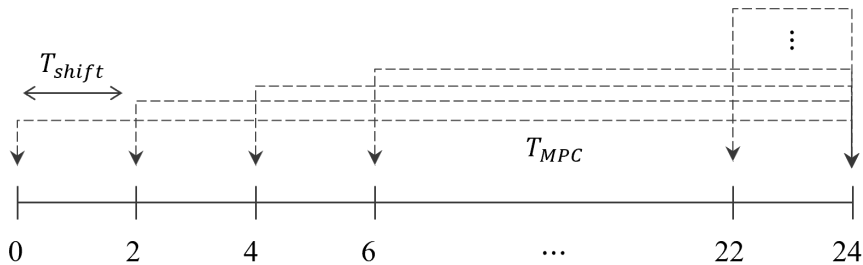
sample



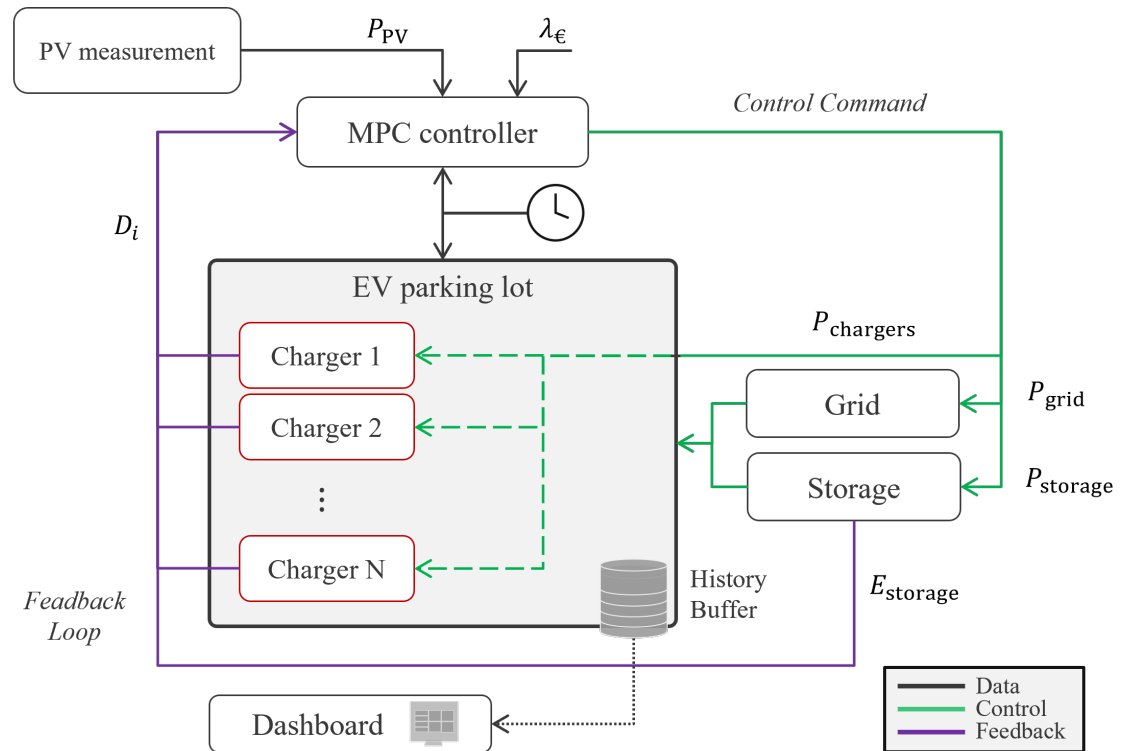
Availability of EVs

MODEL PREDICTIVE CONTROL

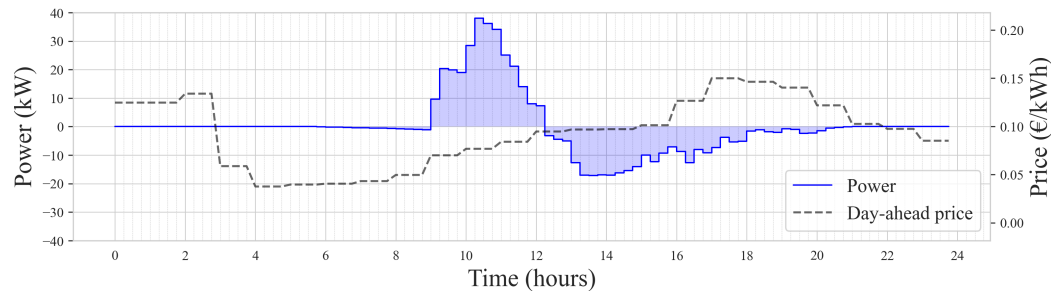
CONTROL OBJECTIVE



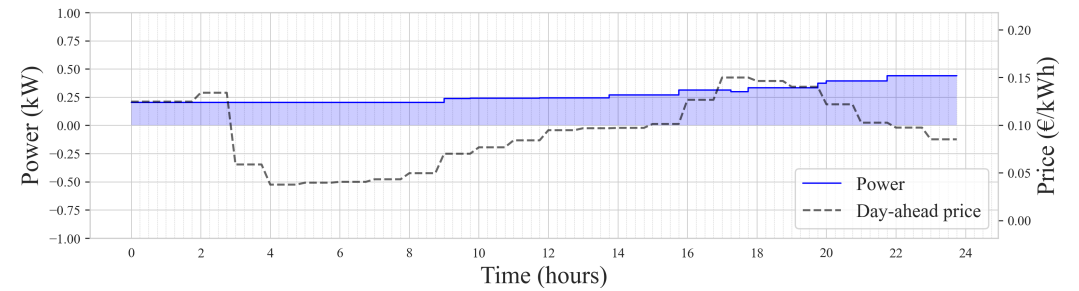
$$\begin{aligned} \text{Minimize } F(\Pi) = & \sum_{t=1}^k \left[P_{\text{grid}}^2(t) \right. \\ & + \left(P_{\text{grid}}^+(t) \times \lambda_{\epsilon}^{\text{buy}}(t) \right. \\ & \quad \left. - P_{\text{grid}}^-(t) \times \lambda_{\epsilon}^{\text{sell}}(t) \right) \cdot \Delta t \\ & \left. + \Delta P(t) \right] \end{aligned}$$



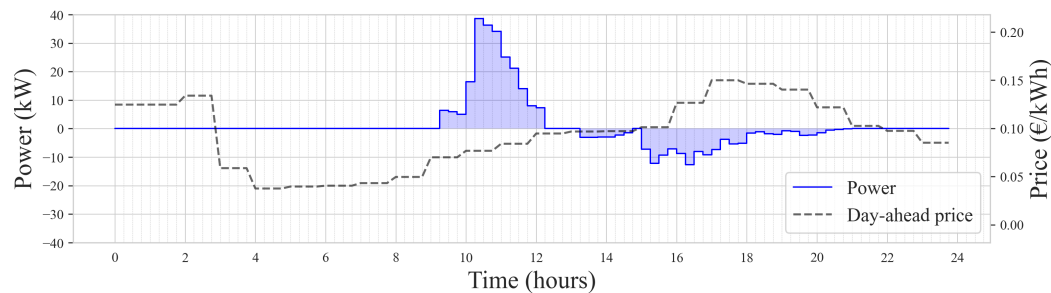
PERFORMANCE ANALYSIS



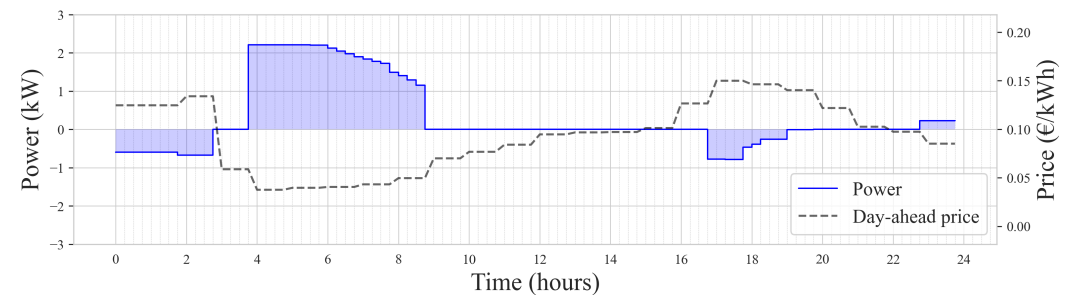
Uncontrolled charging without storage.



Power optimization without financial objective.



Uncontrolled charging with storage.



Power optimization with financial objective.

PERFORMANCE ANALYSIS

PVCS charging method	Private		Public		Workplace
	Weekday	Weekend	Weekday	Weekend	Weekday
Uncontrolled charging without storage	7.690 €	6.278 €	5.159 €	6.944 €	1.252 €
Uncontrolled charging with storage	5.658 €	5.836 €	4.767 €	5.315 €	1.018 €
Open-loop optimization	1.472 €	0.811 €	0.477 €	1.131 €	1.025 €
MPC with shrinking horizon	1.311 €	0.643 €	0.307 €	0.968 €	0.880 €

Daily Electricity cost comparison between PVCS configurations.

PERFORMANCE ANALYSIS

PVCS charging method	Power peak
Uncontrolled charging without storage	38.02 kW
Uncontrolled charging with storage	38.65 kW
Optimization without financial objective	0.44 kW
Optimization with financial objective	2.21 kW

Comparison of daily grid peak power.

PERFORMANCE ANALYSIS

PVCS Charging method	CO ₂ emission
Uncontrolled charging without storage	26.18 kg
Uncontrolled charging with storage	16.66 kg
Open-loop optimization	4.54 kg
MPC with shrinking horizon	3.11 kg

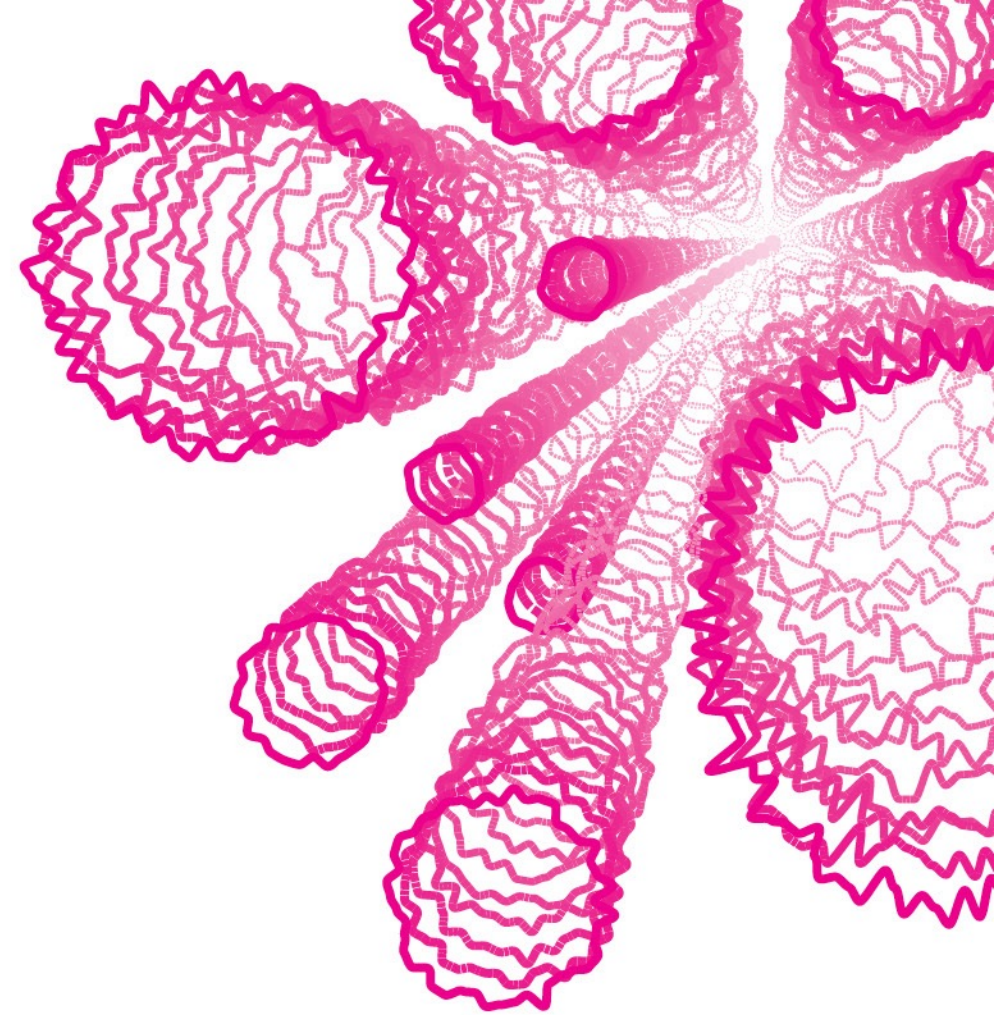
total daily CO₂ emission of PVCS

PERFORMANCE ANALYSIS

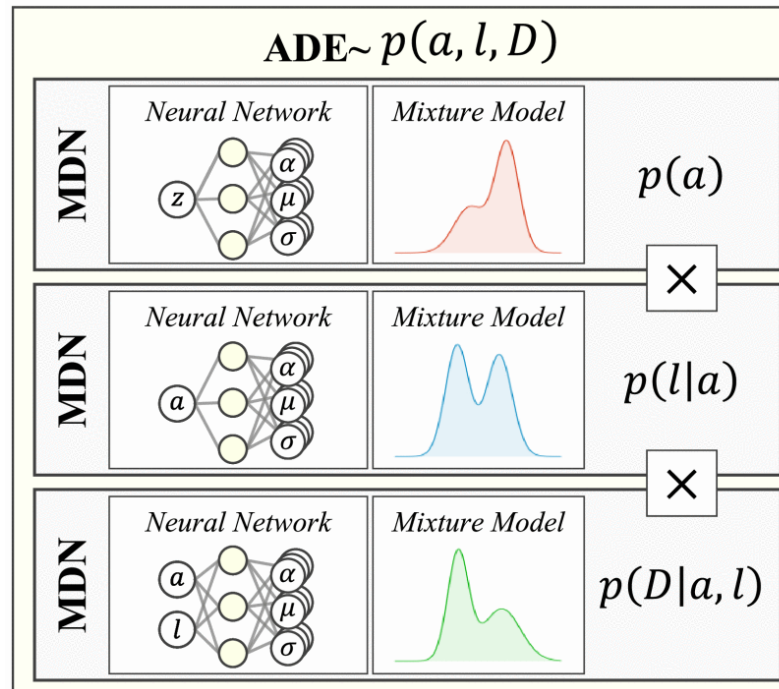
Scale factor S	Number of chargers N	Computation time
$S = 1$	$N = 4$	6.05 s
$S = 2$	$N = 8$	6.93 s
$S = 3$	$N = 12$	19.63 s
$S = 4$	$N = 16$	34.45 s
$S = 5$	$N = 20$	51.79 s

WHAT IF WE LEARN EV DEMAND?

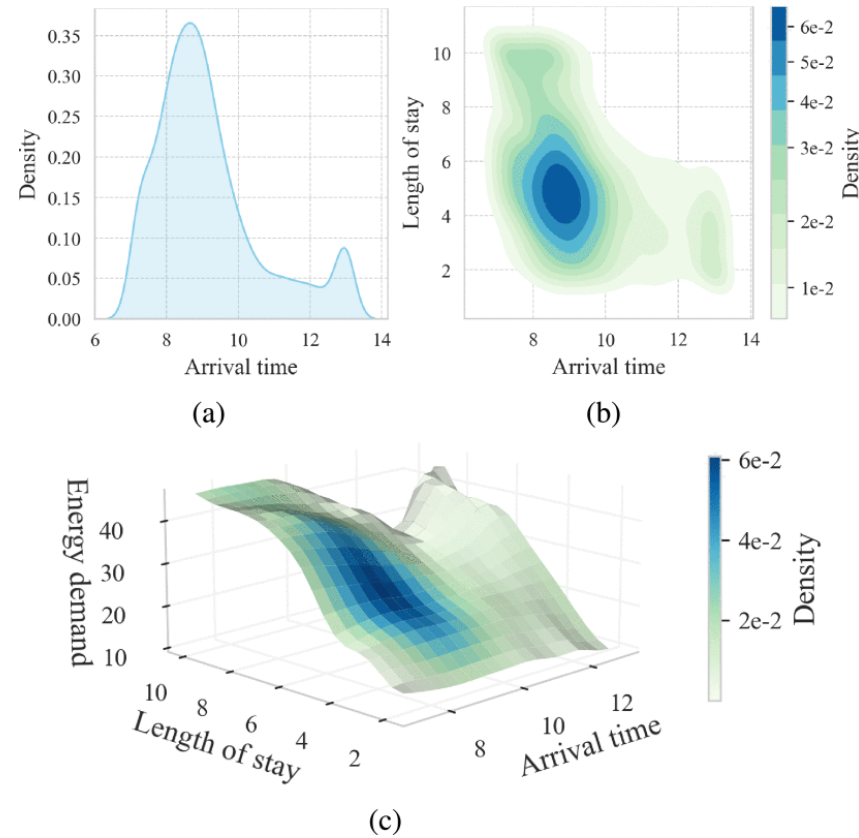
- AND USE IT IN THE DECISION MAKING PROCESS?



LEARNING EV CHARGING BEHAVIOUR WITH MIXTURE DENSITY NETWORKS

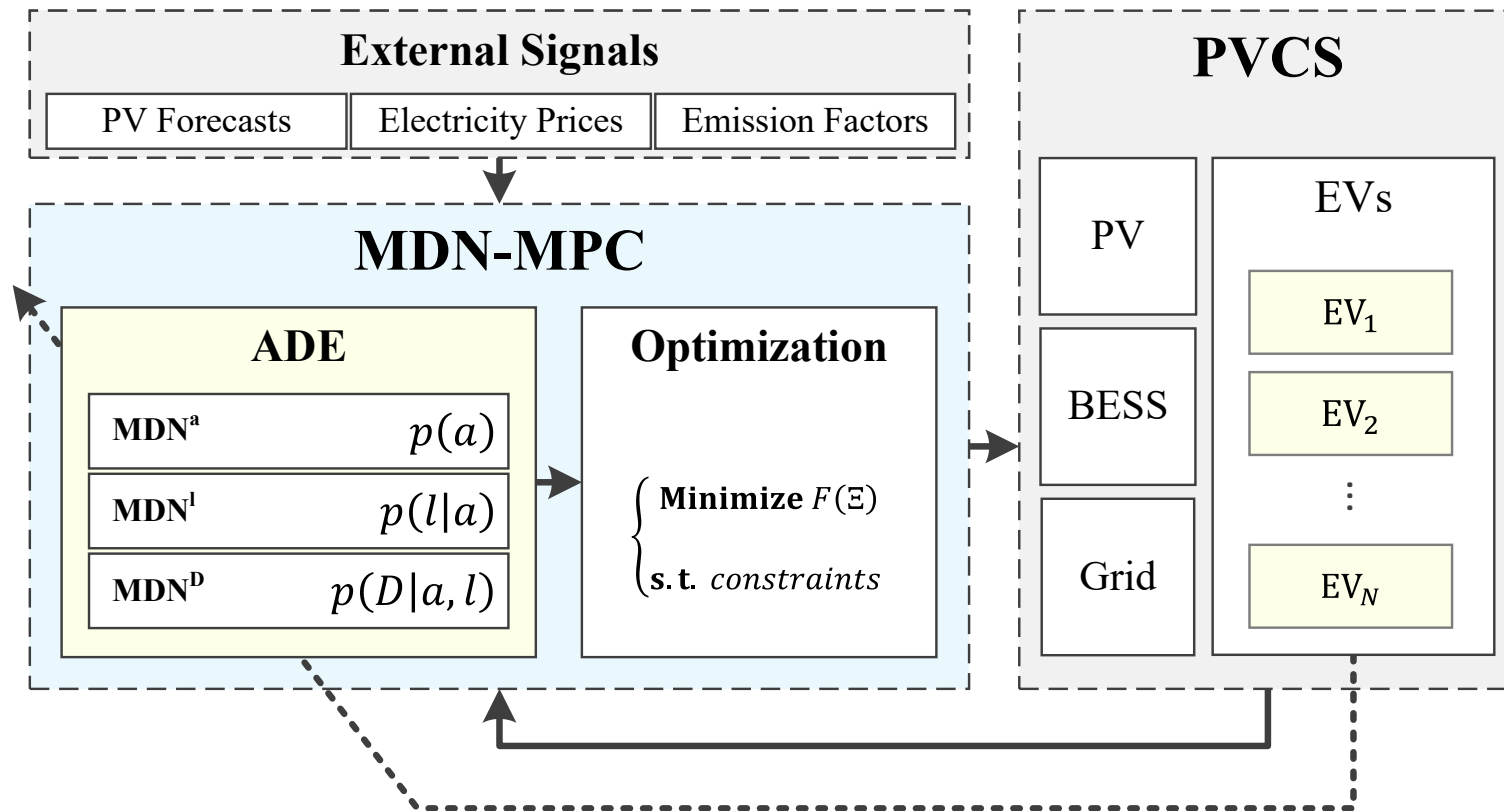


LEARNED DISTRIBUTIONS FOR EV CHARGING BEHAVIOUR

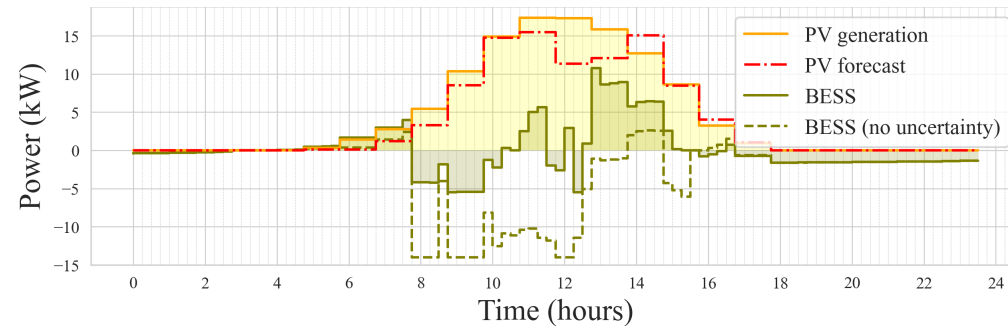


(a) Arrival time: $p(a)$. (b) Length of stay: $p(l|a)$. (c) Energy demand: $p(D|a,l)$.

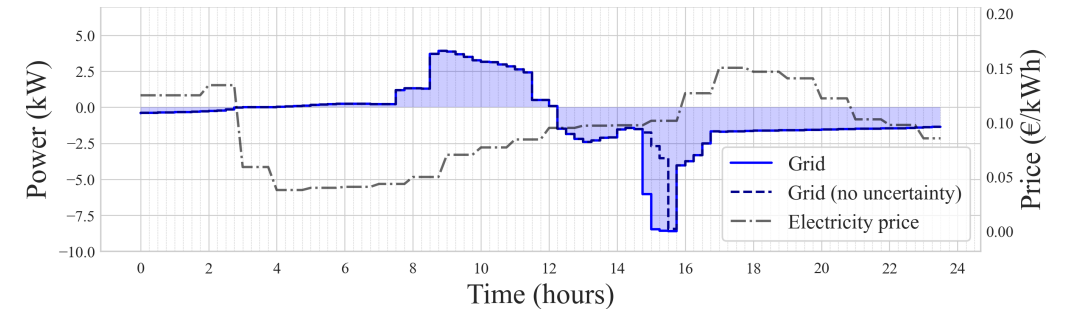
MPC WITH THE LEARNED EV BAHVIOUR



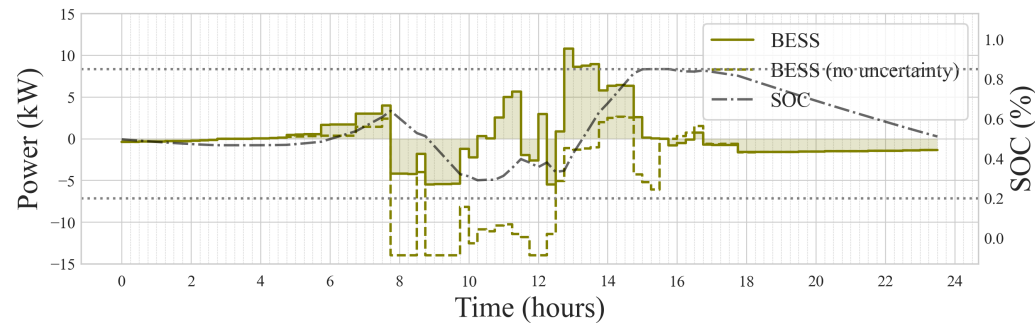
CHARGING CONTROL PERFORMANCE



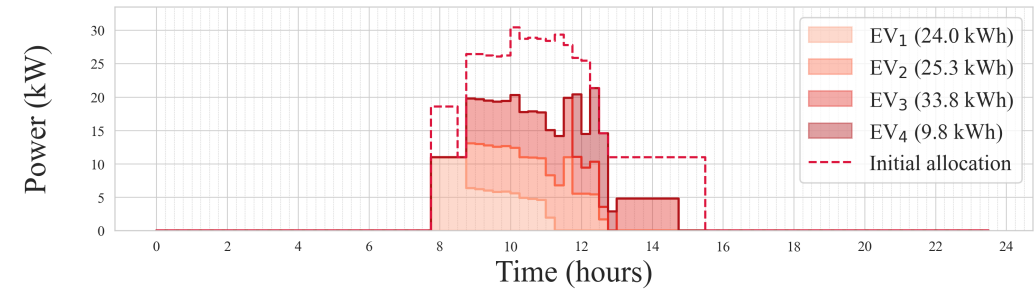
BESS and PV power



Power from grid



BESS power and SOC

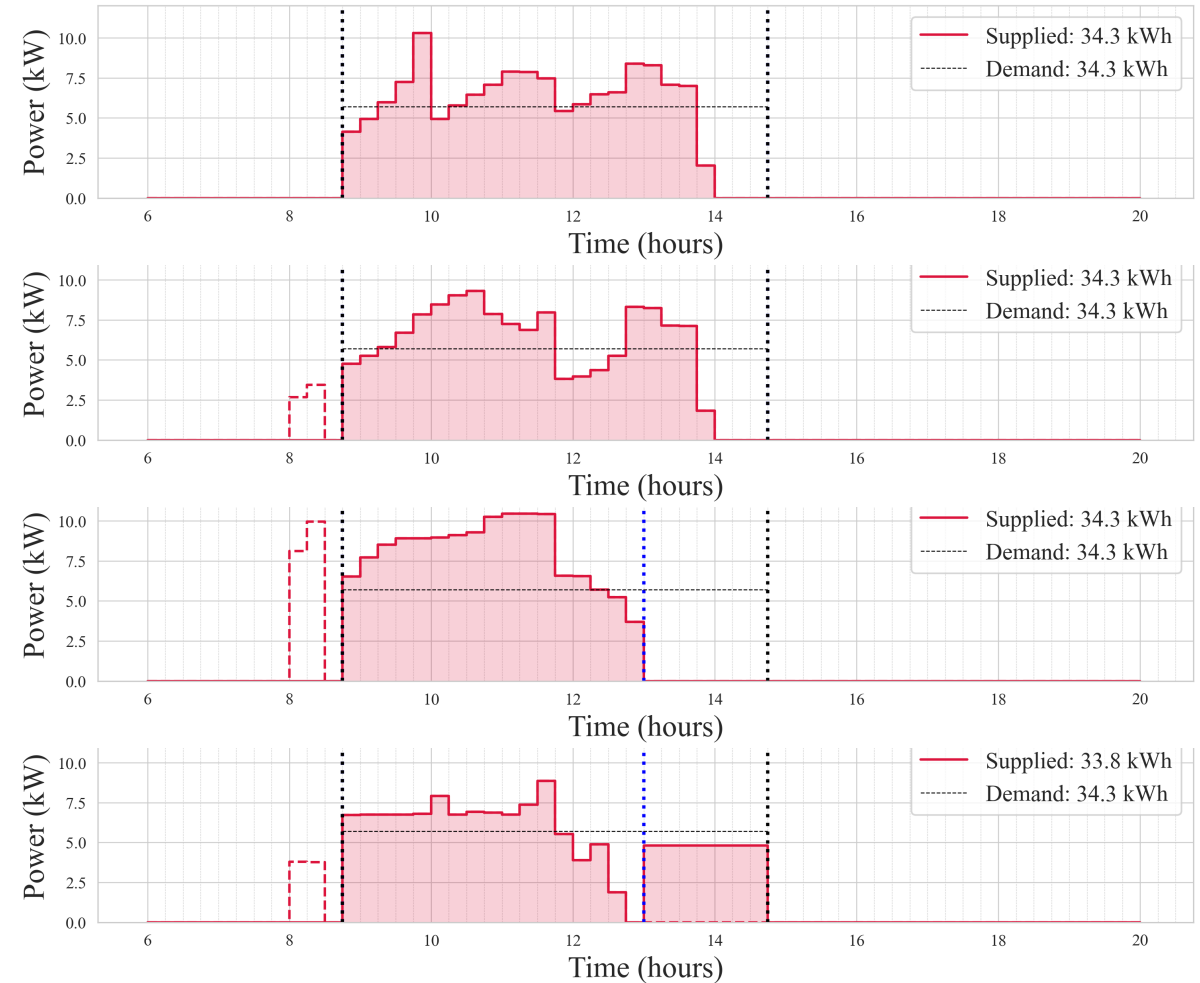


EV charging power

CHARGING CONTROL PERFORMANCE

MDNs In EV Uncertainty Scenarios

- Scenario 1: EV arrivals, lengths of stay, and demands are known
- Scenario 2: EV arrivals are uncertain, while lengths of stay and demands are known
- Scenario 3: EV arrivals and lengths of stay are uncertain, while demands are known
- Scenario 4: EV arrivals, lengths of stay, and demands are uncertain

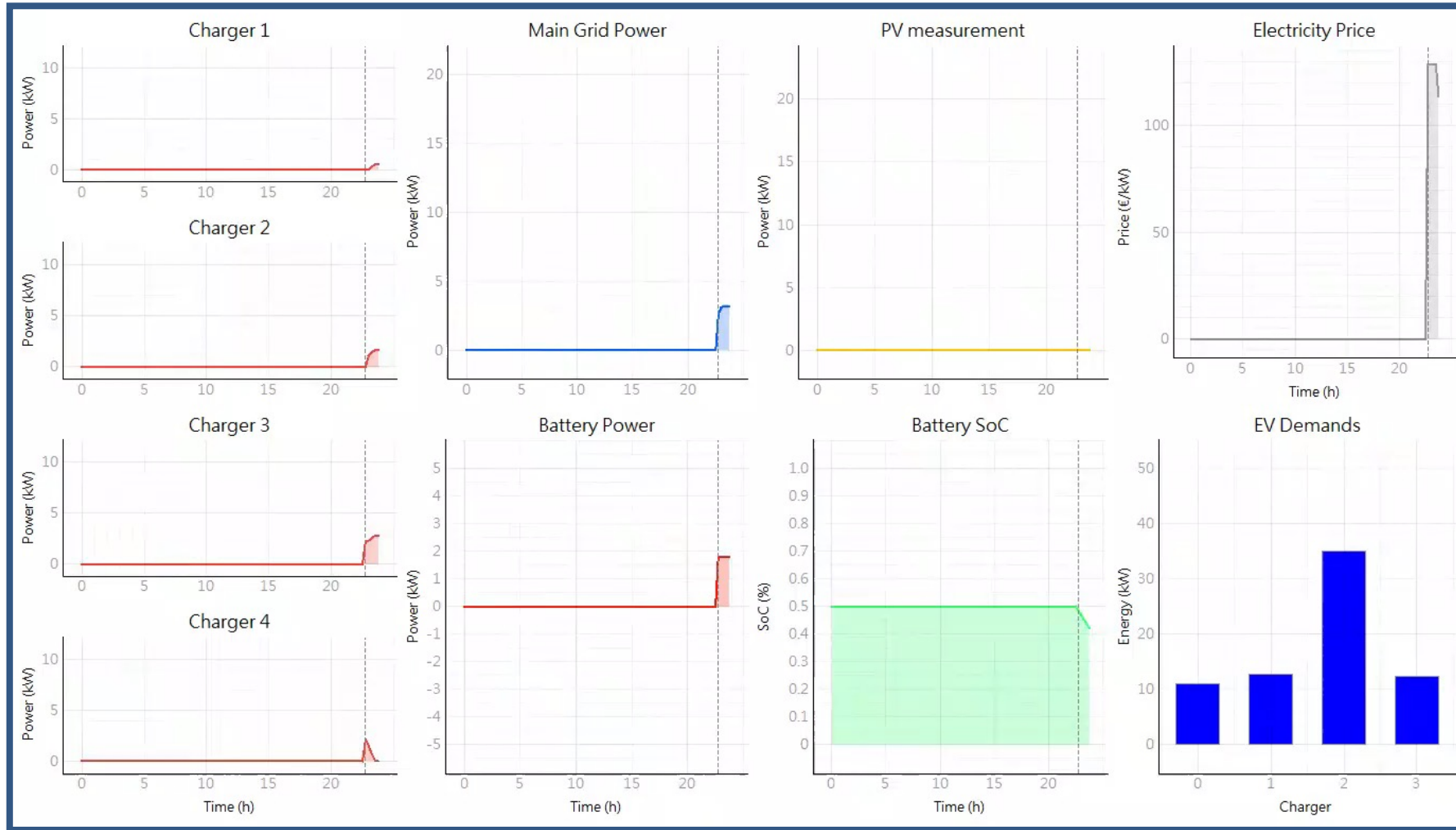


Charging Control Performance

EV Uncertainty Scenario	Metric	MIQP	MPC	MDN-MPC	Deterministic
Scenario 1: (a, l, D) - No Uncertainty	Cost (€)	3.20	3.11	3.11	2.85
	Emission (kg)	5.51	6.01	6.01	5.06
	Peak (kW)	9.69	6.46	6.46	4.76
	Unmet demand (kWh)	6.38	3.78	3.78	3.71
Scenario 2: $(\tilde{a}, l, D)$ - Arrivals are uncertain	Cost (€)	3.19	3.00	3.21	—
	Emission (kg)	3.37	3.89	6.17	—
	Peak (kW)	10.97	8.08	7.11	—
	Unmet demand (kWh)	12.13	8.25	3.84	—
Scenario 3: $(\tilde{a}, \tilde{l}, D)$ - Arrivals and lengths of stay are uncertain	Cost (€)	4.27	3.77	3.50	—
	Emission (kg)	4.22	4.77	6.43	—
	Peak (kW)	13.30	10.77	8.54	—
	Unmet demand (kWh)	13.17	8.81	4.93	—
Scenario 4: $(\tilde{a}, \tilde{l}, \tilde{D})$ - Arrivals, lengths of stay and demands are uncertain	Cost (€)	3.95	4.36	3.26	—
	Emission (kg)	3.60	4.60	4.34	—
	Peak (kW)	12.78	13.94	10.59	—
	Unmet demand (kWh)	18.81	13.21	8.96	—

A. Heydarian Ardakani, B. Nijenhuis, J. Hurink, I. Gibson and E. Shirazi, "MDN-MPC: Learning EV Charging Behavior With Mixture Density Networks for Controlling PV Charging Stations," in IEEE Transactions on Transportation Electrification, vol. 12, no. 2, pp. 3525-3535, April 2026, doi: 10.1109/TTE.2026.3656021 <https://ieeexplore.ieee.org/abstract/document/11358917>

LIVE DASHBOARD

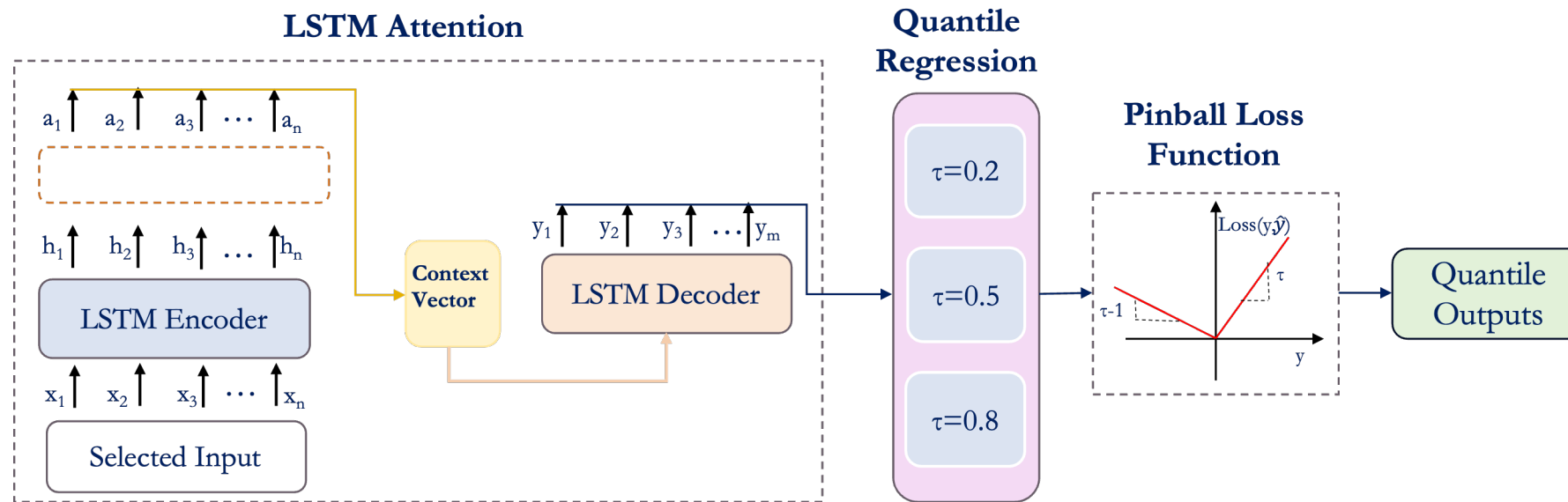


LIVING LAB 2: A.S.R. SMART CAR PARK



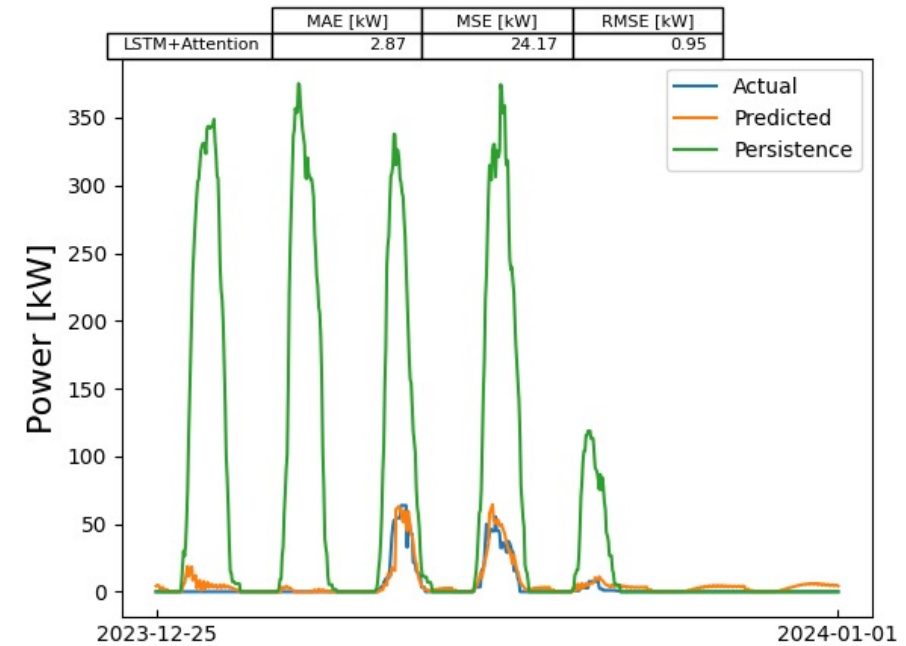
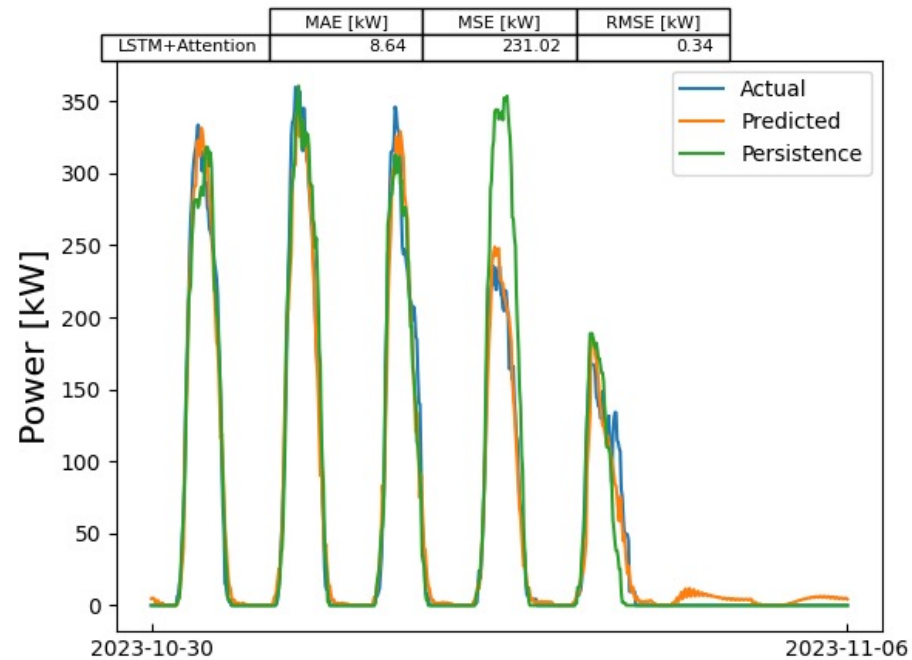
- EU's largest EV charging station (2021) with 250 smart bi-directional charging stations
- A roof with more than 2,000 solar panels which can provide for 4 million electric kilometres a year.

EV CHARGING DEMAND PROBABILISTIC FORECAST

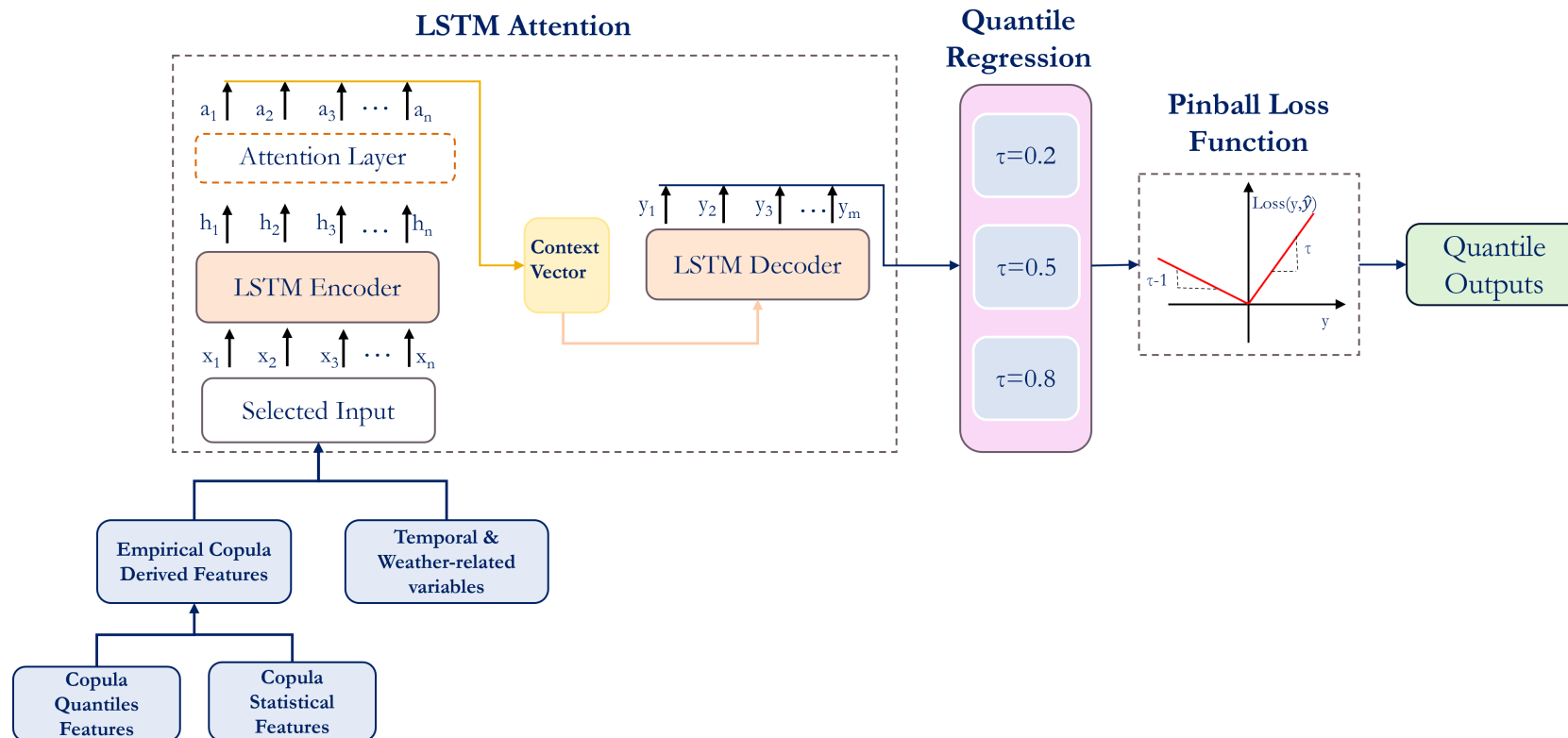


S. Matrone, AH. Ardakani, E. Ogliari, E. Shirazi, S Leva (2025, June). Probabilistic forecast of EV charging demand using quantile regression and lstm with attention mechanism. In *Proceedings of the 16th ACM International Conference on Future and Sustainable Energy Systems* (pp. 1002-1004).

EV CHARGING PROBABILISTIC FORECAST

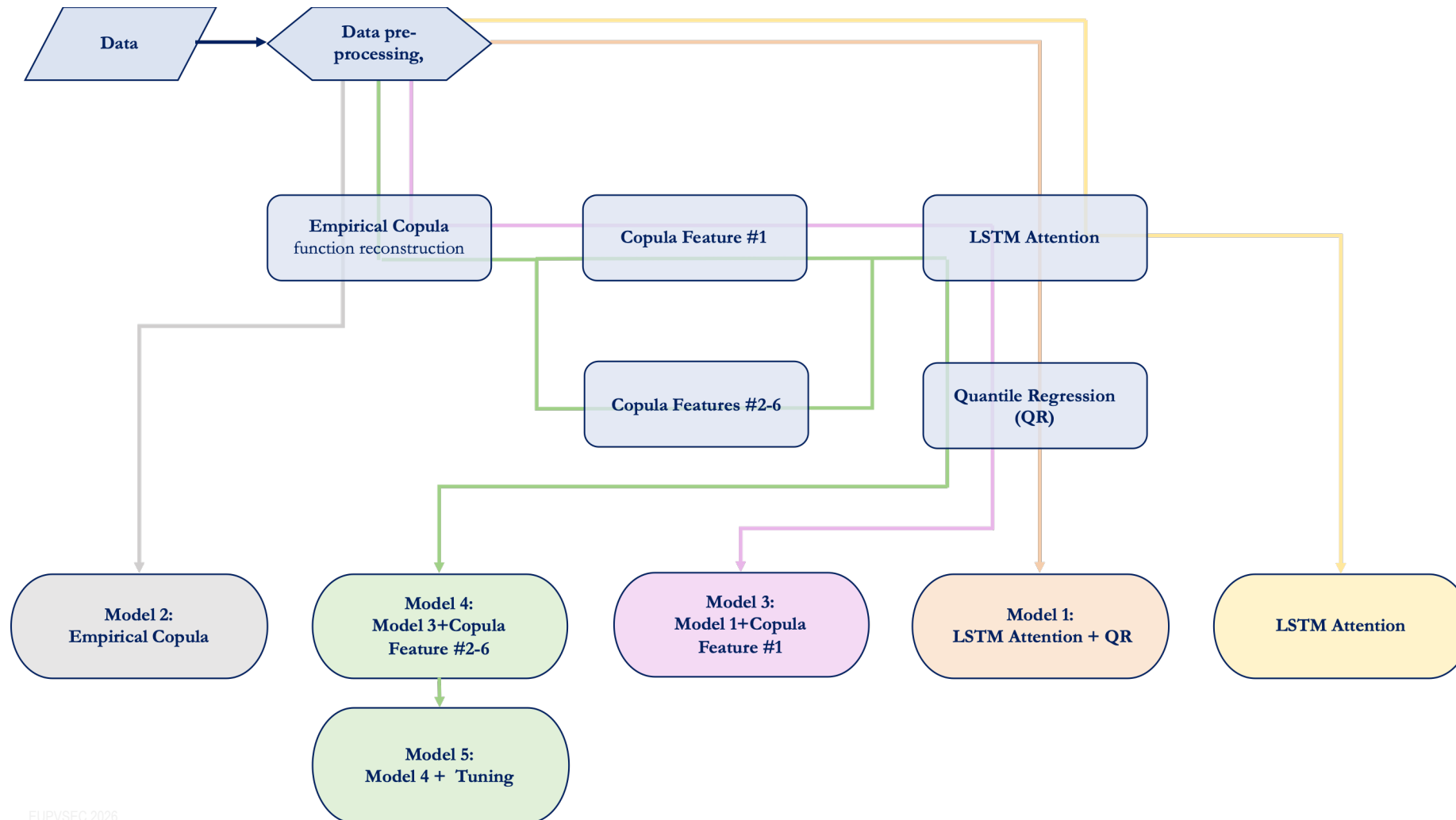


COPULA INFORMED QUANTILE REGRESSION FOR PROBABILISTIC EV CHARGING DEMAND FORECASTING



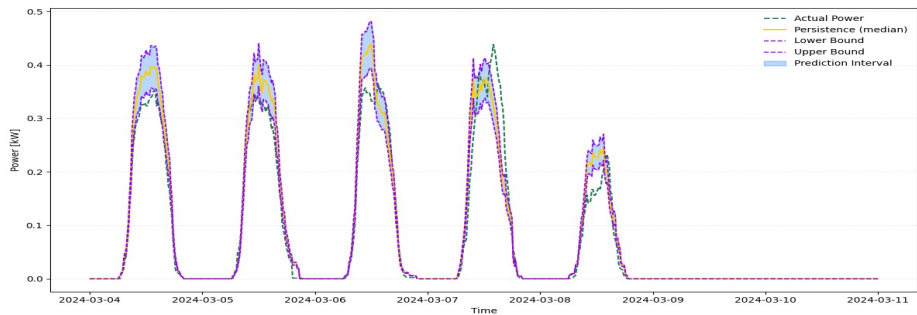
S. Matrone, J. Han, E. Ogliari, E. Shirazi, "Copula Informed Quantile Regression for Probabilistic EV Charging Demand Forecasting", Under Review.

LET'S ADD SOME FEATURES!

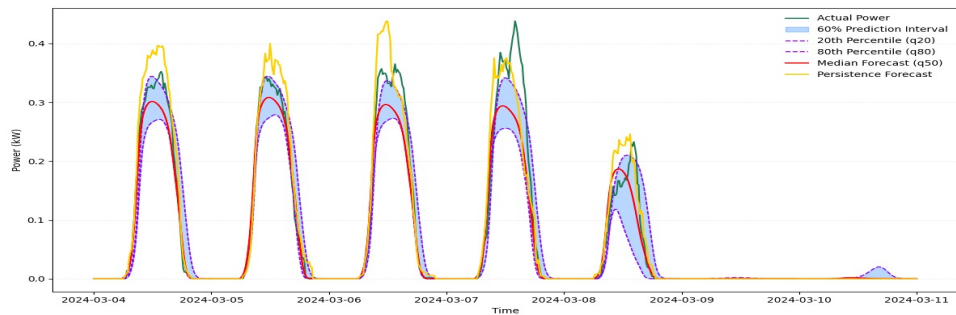


PROBABILISTIC FORECAST OF EV CHARGING DEMAND

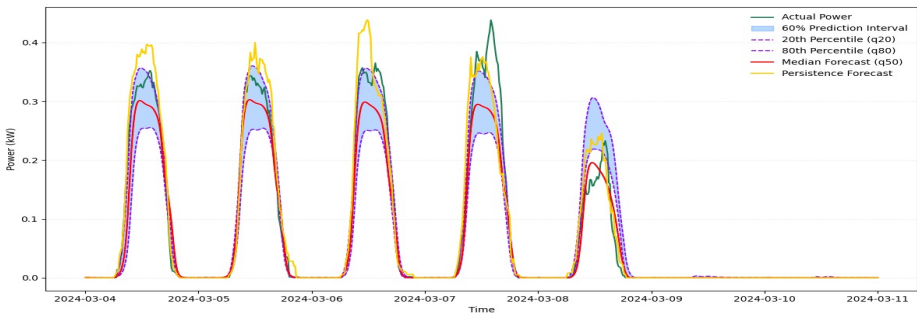
Benchmark



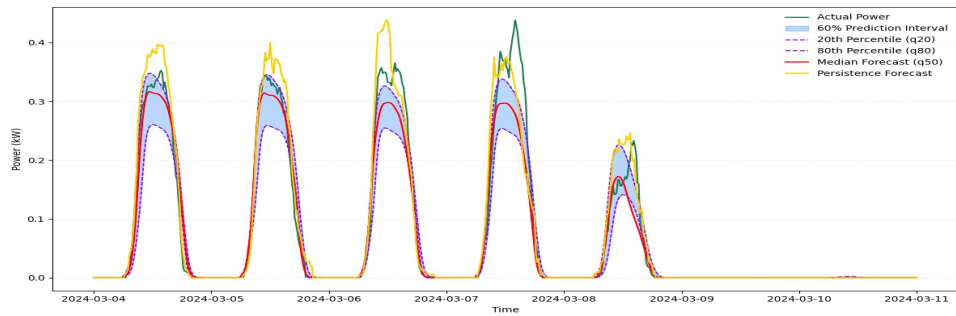
Model 3



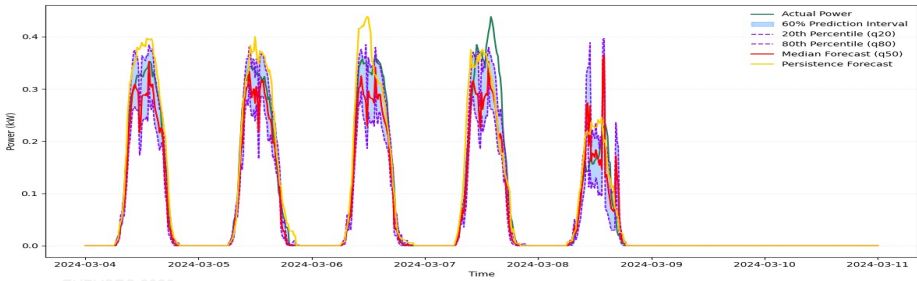
Model 1



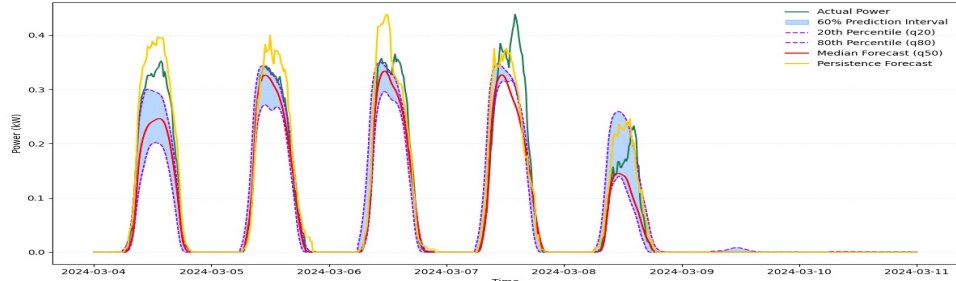
Model 4



Model 2



Model 5



COMPARISON OF FORECASTING MODELS

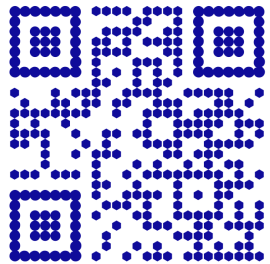
Metric	Model 1	Model 2	Model 3	Model 4	Model 5	Benchmark
PL (q20) [kW]	6.80	7.97	6.90	6.12	5.56	8.80
PL (q50) [kW]	10.55	4.82	8.48	9.11	8.93	10.85
PL (q80) [kW]	6.92	6.39	7.73	9.74	7.81	9.95
WIS [kW]	37.16	37.97	36.74	39.5	35.35	171.61
C [%]	69.78	91.82	57.68	52.85	62.25	64.63
S [kW]	22.45	40.80	23.24	23.84	24.76	13.24

Model	Interpretation
Model 1	Reasonably precise, but somewhat over-conservative
Model 2	Quantile accuracy looks good individually, but intervals are far too wide / over-dispersed
Model 3	Very balanced probabilistic forecast
Model 4	Under-dispersed / insufficient upper-tail performance
Model 5	Strongest overall balance of calibration and probabilistic accuracy

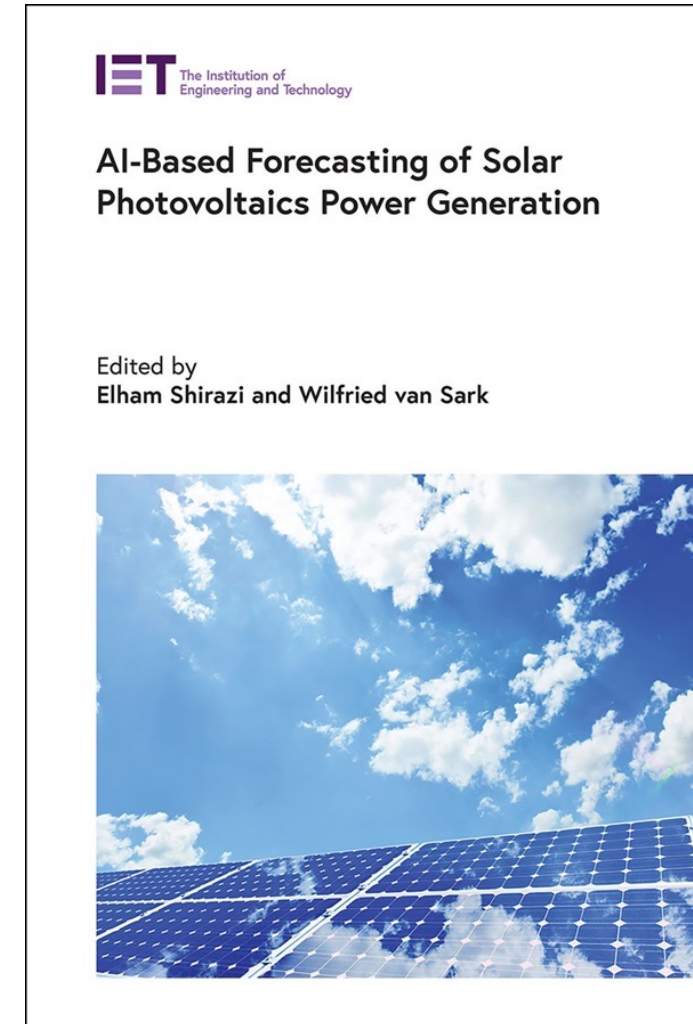
MORE IN OUR BOOK

AI-Based Forecasting of Solar Photovoltaics Power Generation

Elham Shirazi, and Wilfried van Sark



EPUB3 ISBN: 9781807050108, <https://doi.org/10.1049/PBPO268E>



QUESTIONS?

FEEL FREE TO SEND ME AN EMAIL:

E.SHIRAZI@UTWENTE.NL

