Data Driven Models for Building Occupancy Estimation

Omid Ardakanian
University of Alberta

joint work with Shadan Golestan and Sepehr Kazemian

ACM e-Energy 2018

Motivation

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  - occupant count determination [harder]
- Little work has been done on benchmarking occupant count determination techniques in multiple buildings

Why fine-grained occupancy information is needed?

- Security
- Workspace utilization
- Smart lighting
- Demand-controlled filtration and ventilation

Data-driven vs. physics-based models

Data-driven vs. physics-based models

- High-dimensional physics-based models for heat transfer
  - must be customized per zone
  - **Challenge:** distinguish internal heat gains due to occupancy from other latent factors
- Data-driven models
  - training these models is straightforward, requiring only a few weeks of ground truth data
  - can adapt to the variable occupancy pattern of each room
  - **Challenge:** fuse data from various sensing modalities

Our approach

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- Study the sensitivity of the results to the maximum occupancy of a room

Data sets

Data Sets	Sensors
Building 1 [1]	VOC: Volatile organic compounds concentration
	BLE: #BLE beacons in the range of the receiver
	CAL: Calendar with scheduled events
	DAY: Flag indicating a weekday or a weekend
Building 2 [2]	CO2: Carbon-dioxide concentration
	Damper position: VAV Damper position

[1] F. Fiebig, et al., Detecting Occupancy in Smart Buildings by Data Fusion from Low-cost Sensors: Poster Description, e-Energy 17

[2] FC Sangogboye, et al., Performance comparison of occupancy count estimation and prediction with common versus dedicated sensors for building model predictive control, Building Simulation 17

Particle Filtering — Basic idea

$$
\begin{aligned}
p(X_{0:t}|Z_{1:t}) &= p(X_t|Z_t)p(X_t|X_{t-1})p(X_{0:t-1}|Z_{1:t-1}),\\
&\overset{Bayes}{=} \eta\, p(Z_t|X_t)p(X_t|X_{t-1})p(X_{0:t-1}|Z_{1:t-1}),
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Particle Filtering — Basic idea

categorical random variable
modelling the number of occupants at t

m-dimensional random variable
modelling measurement of m sensors at t

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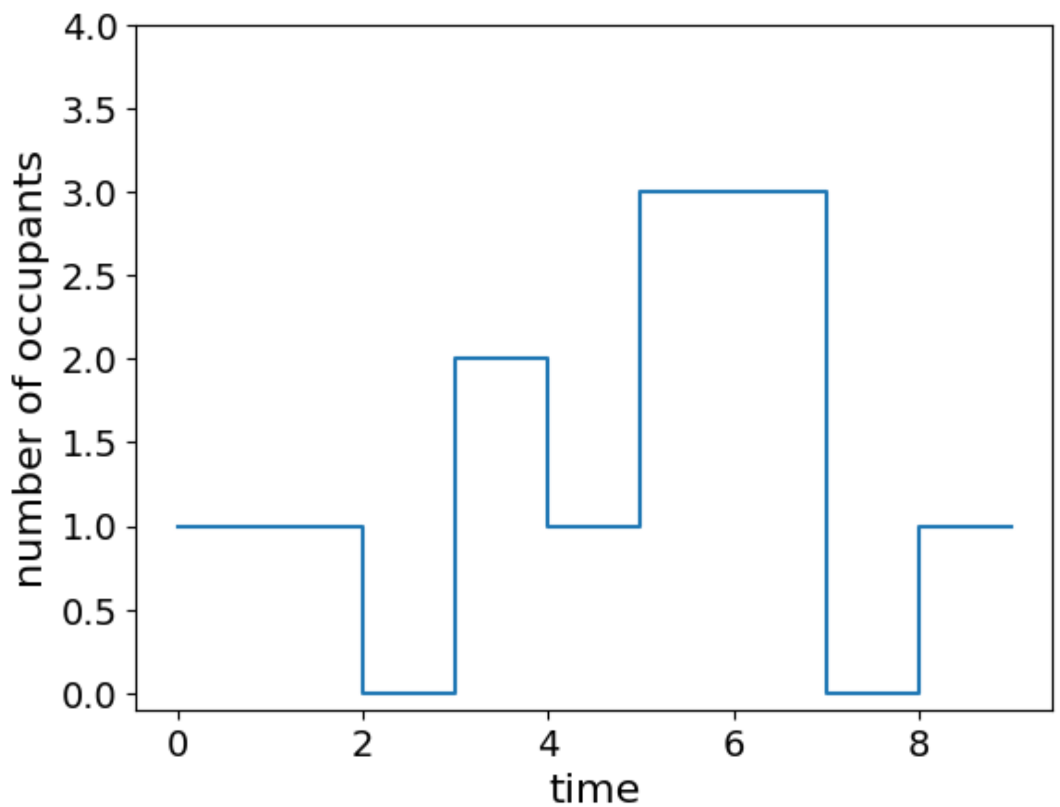
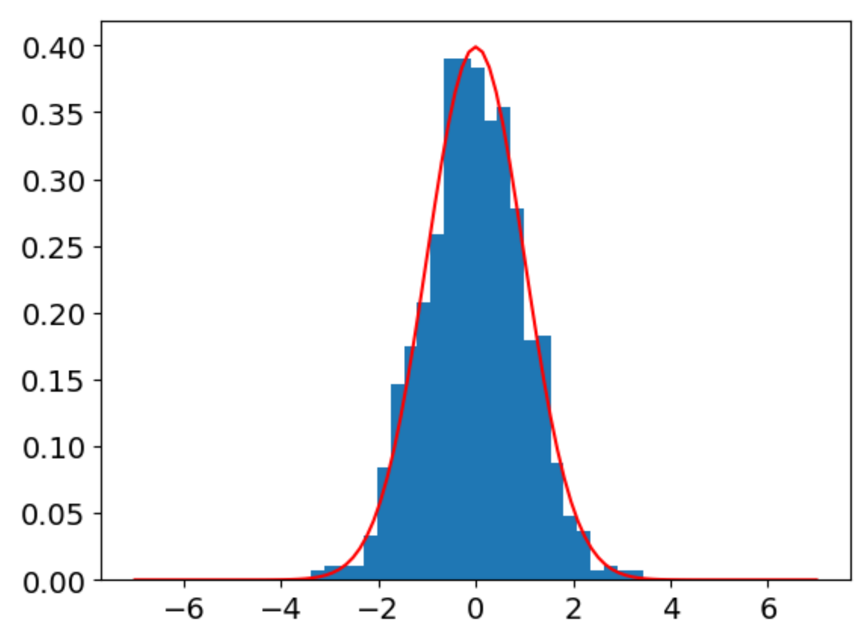
1. *learn the state transition model and the measurement model from ground truth data*



$$(Z_t^i|X_t = k) \sim \mathbf{G}(\ \widehat{\mathbb{E}}(Z_t^i|X_t = k), \widehat{\mathbb{V}}(Z_t^i|X_t = k)\ ),$$



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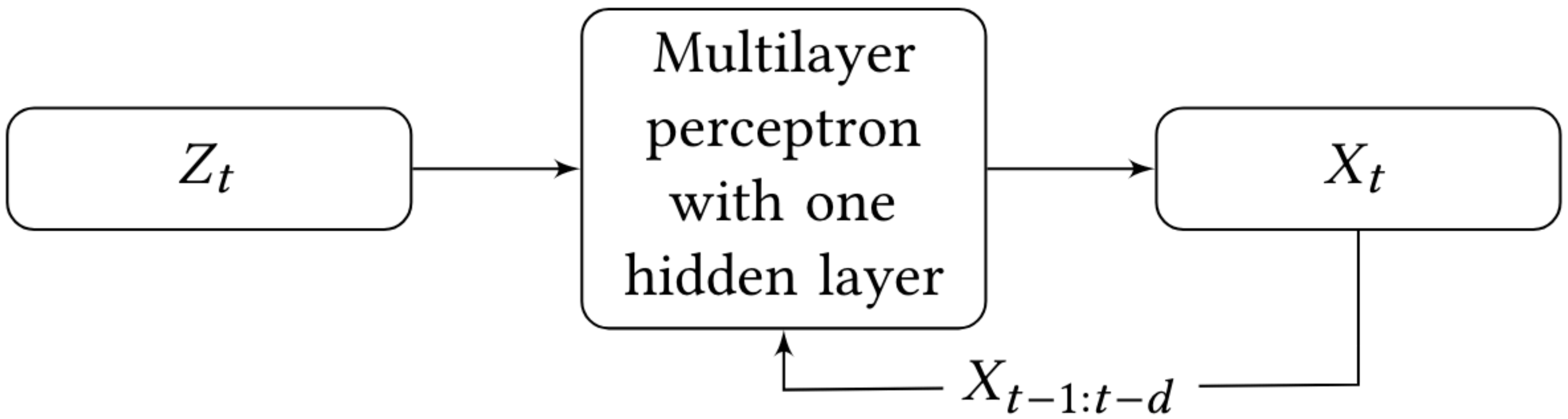
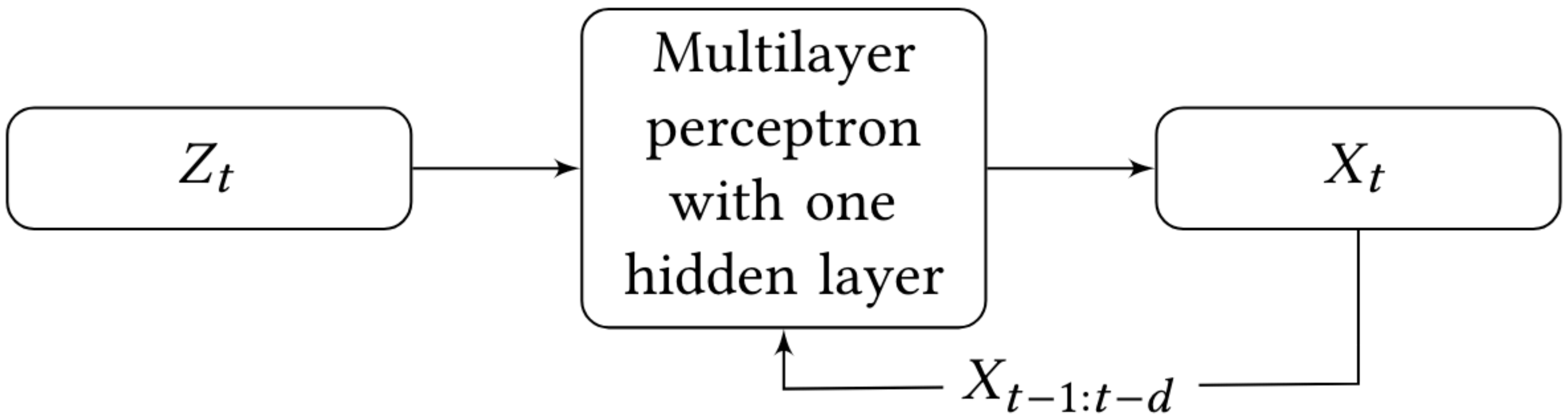
6. *go to step 3*

Time Series Neural Network — Basic idea



Time Series Neural Network — Basic idea

nonlinear autoregressive exogenous model (NARX)



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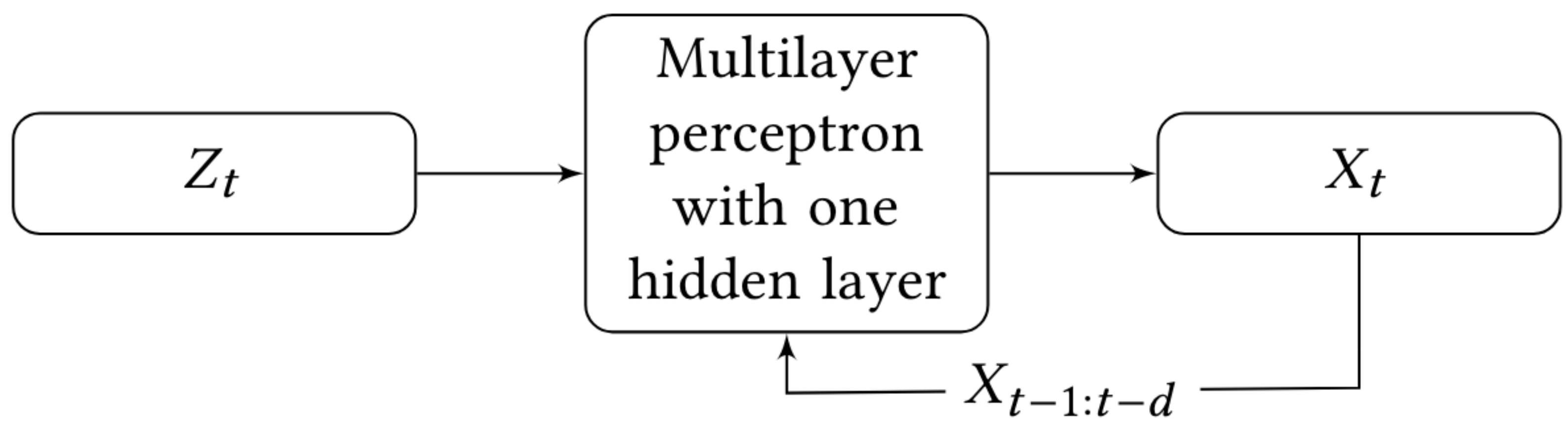


$$X_t = \boldsymbol{F}(X_{t-1}, \ldots, X_{t-d}, Z_t)$$

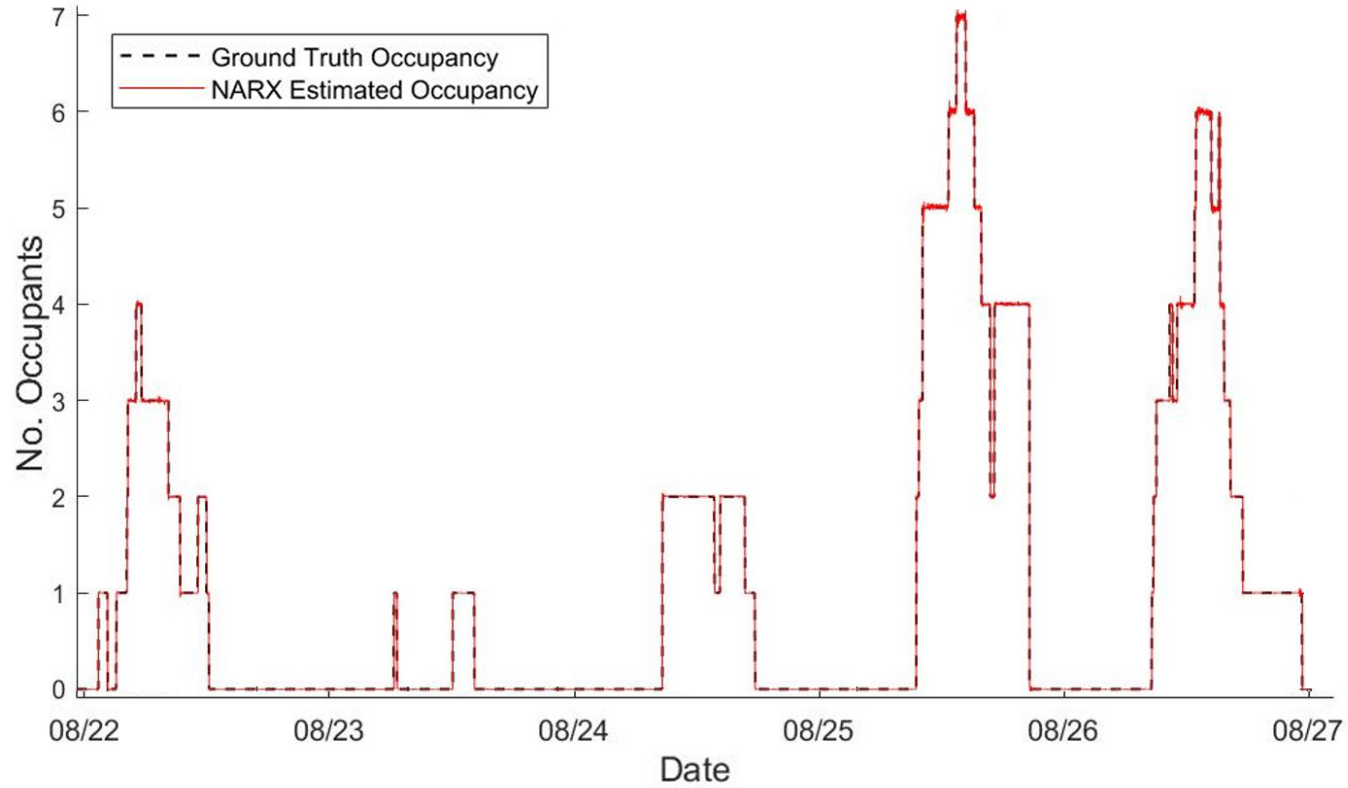
last d values of the same series

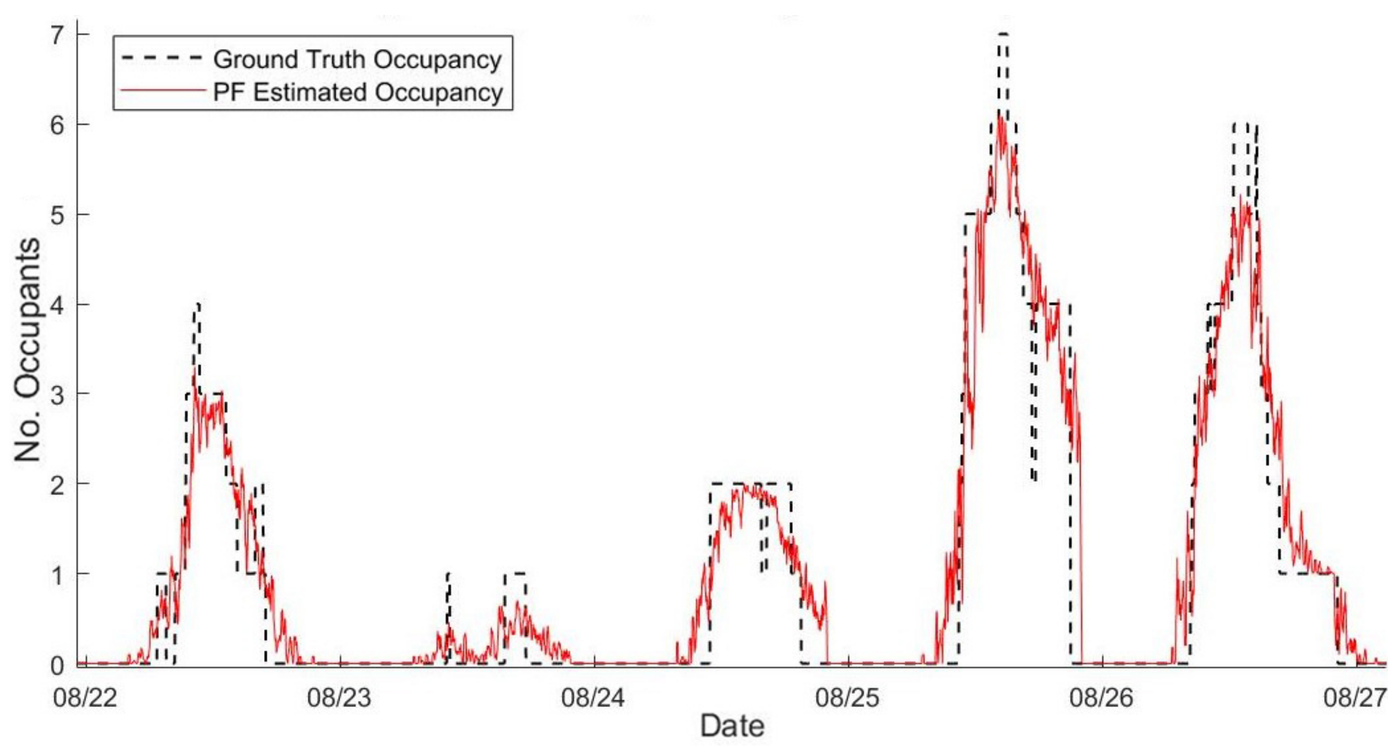
current value of the driving (exogenous) series

Summary of results (RMSE)

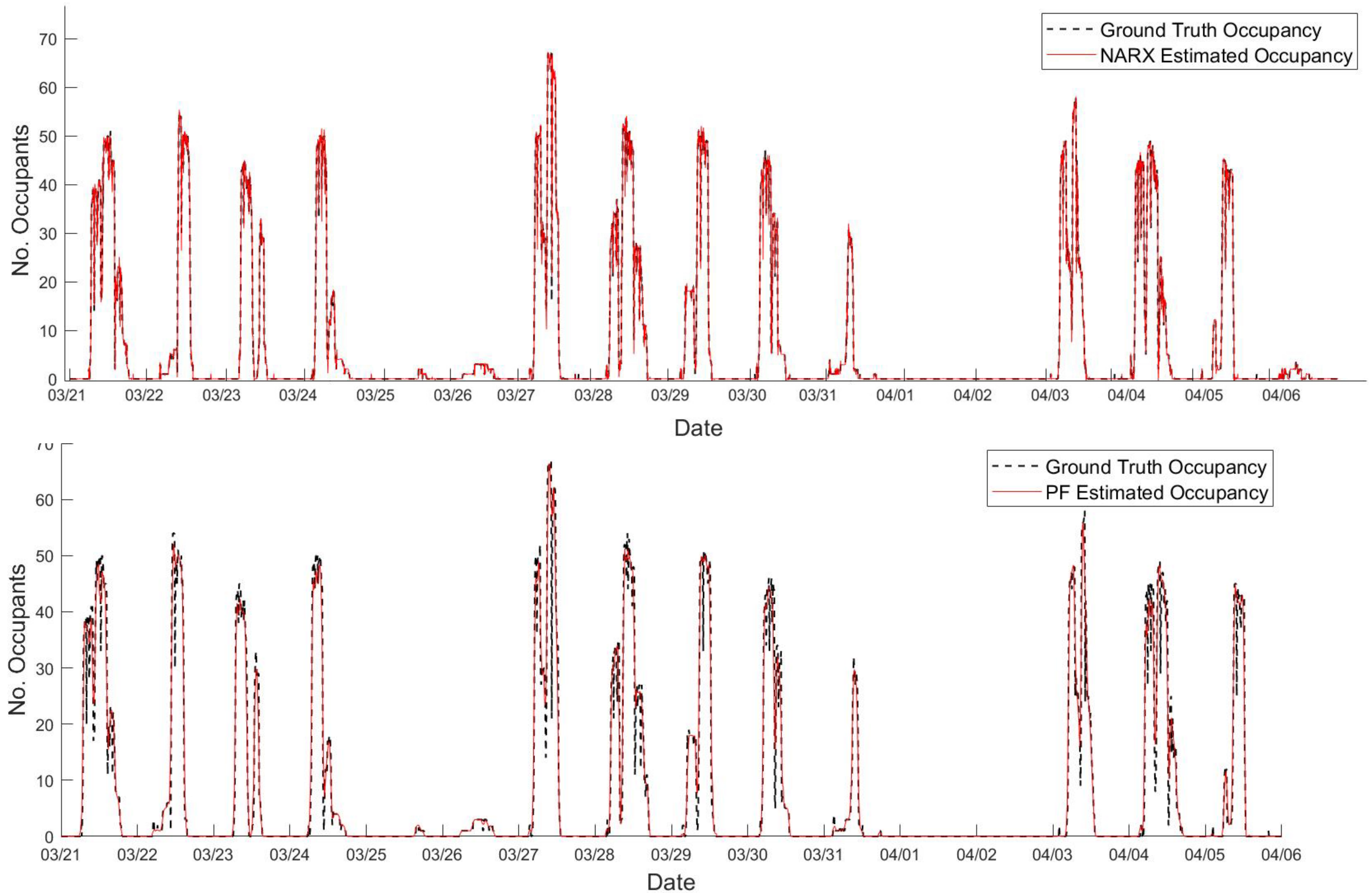
	Building 1	Building 2			
		Room1	Room2	Room3	Room4
PF	0.4	1.5	0.8	1.4	2.9
NARX	0.3	0.4	0.4	0.5	0.8
max no. occupants	7	29	35	39	67
avg no. occupants	0.4	2.7	2.5	3.6	7.4
peak-to-avg occupancy ratio	0.06	0.09	0.07	0.09	0.11

Example results - Building1





Example results - Room1/Building2



NARX results are more stable

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