Establishment of Enhanced Load Modeling by Correlating with Occupancy Information

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1 Background

- Load consumption is time-varying due to human behaviors, different load models may be found in different time periods.
- Conventional load modeling methods using measurement data in a certain period may not be able to capture the time-varying load behaviors that may be affected by the real environment, especially by an irregular movement of human activities.
- Under normal circumstances, the power consumption in a load area is expected to change at different time frames that are influenced by their existence closer to the metering points.

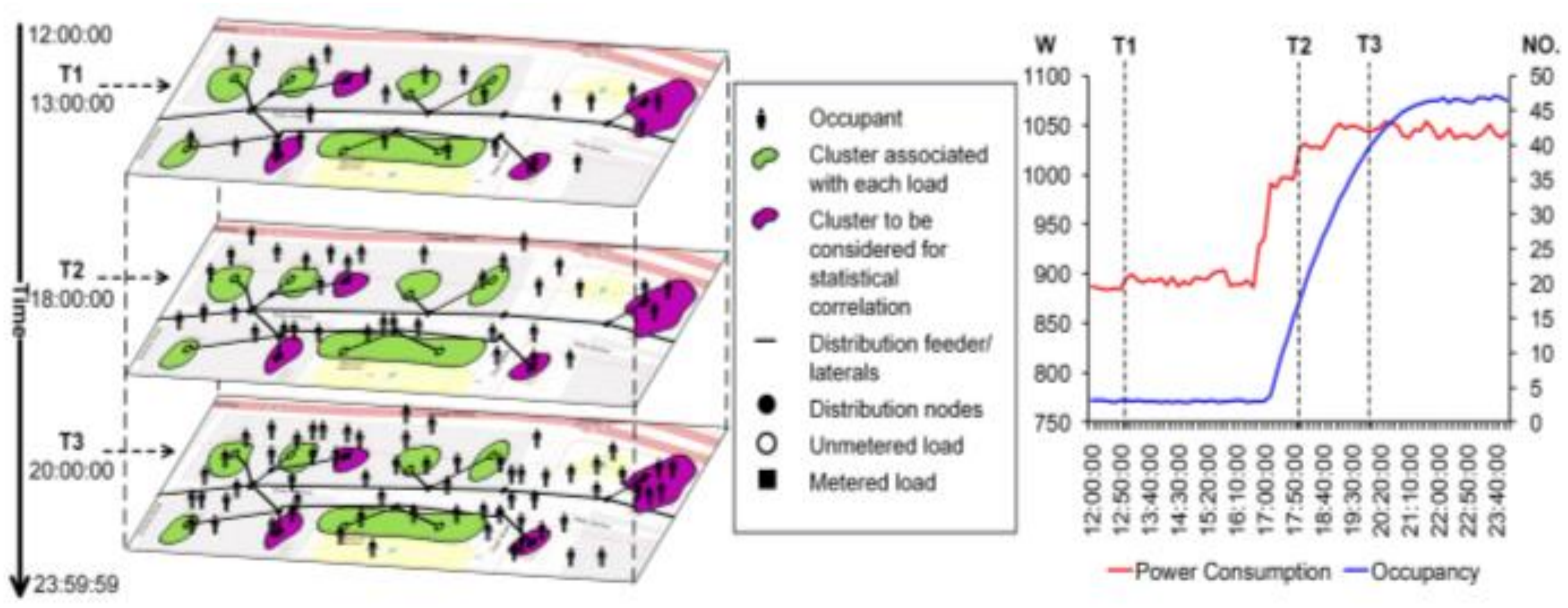


Fig. 1. Ideal correlation of human movements and electricity consumption within a partial distribution feeder.

2 Enhanced Load Modeling Framework

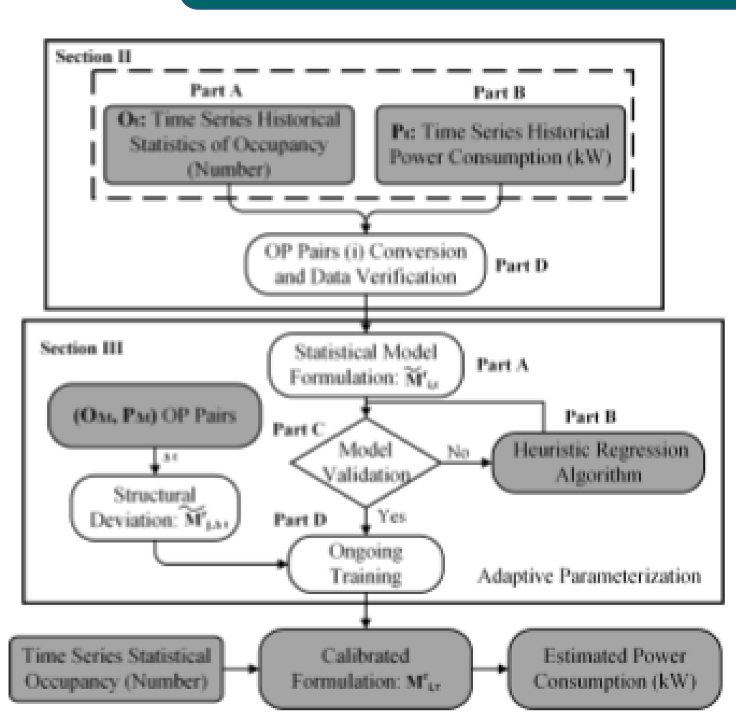
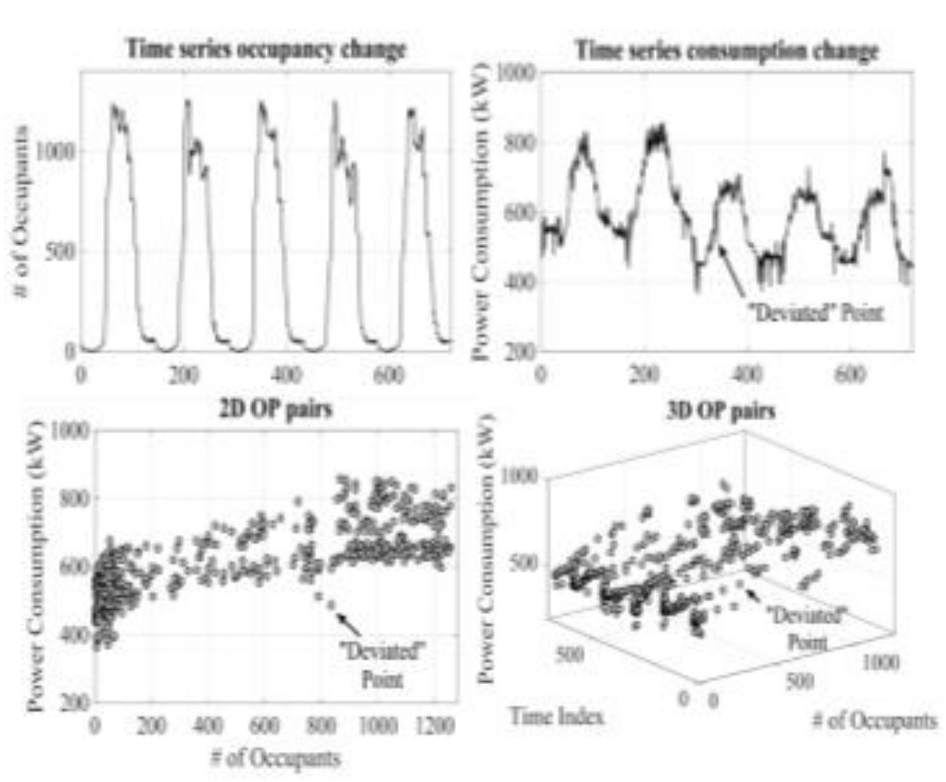


Fig. 2. Flowchart of the proposed correlation framework.



3 Heuristic Regression Model

Algorithm 1 Heuristic Regression Algorithm

Initialization:

S: A set of OP paired points based on O_t and P_t.
S': A test set for cross-validation.
R: A training set to construct a regression model.
$f_h(\cdot)$: Iteration function of heuristic regression.
CM_m: A set of candidate models, where m is the index for candidate models, $m = 1, 2, \cdots$
ν: Test criteria to validate a regression model.
n: Number of elements in R.
$n_{\min}$: Minimum number of elements in R can partition set in the heuristic regression algorithm.
λ, ρ: Adjustment parameters.

Input: O_t, P_t

1: Construct S.

Iteration Process: Extract S' from S and left R.

2: **if** $f_h(R, CM_m, \nu)$ satisfy ν **then**
3: $\quad \widetilde{M^r}(R,t) \leftarrow f_h(R, CM_m, \nu)$;
4: $\quad$ **return** $\widetilde{M^r}(R,t)$;
5: **else**
6: $\quad$ **while** $n \geq n_{min}$ **do**
7: $\quad\quad R_{\text{Part1}} \leftarrow R(1, 2, \cdots, \lambda)$,
$\quad\quad R_{\text{Part2}} \leftarrow R(\lambda+1, \cdots, n)$.
8: $\quad\quad$ Do $f_h(R_{\text{Part1}}, CM_m, \nu)$, $f_h(R_{\text{Part2}}, CM_m, \nu)$
9:

$$\widetilde{M^r}(R,t) = \begin{cases} \widetilde{M^r_{\text{Part1},t}} = f_h(R_{\text{Part1}}, CM_m, \nu), R \in R_{\text{Part1}} \\ \widetilde{M^r_{\text{Part2},t}} = f_h(R_{\text{Part2}}, CM_m, \nu), R \in R_{\text{Part2}}. \end{cases}$$

10: $\quad$ **end while**
11: **end if**
12: **if** No $\widetilde{M^r}(R,t)$ generated. **then**
13: $\quad$ Reduce $n_{\min}$ by ρ;
14: $\quad$ Do $f_h(R, CM_m, \nu)$
15: **end if**

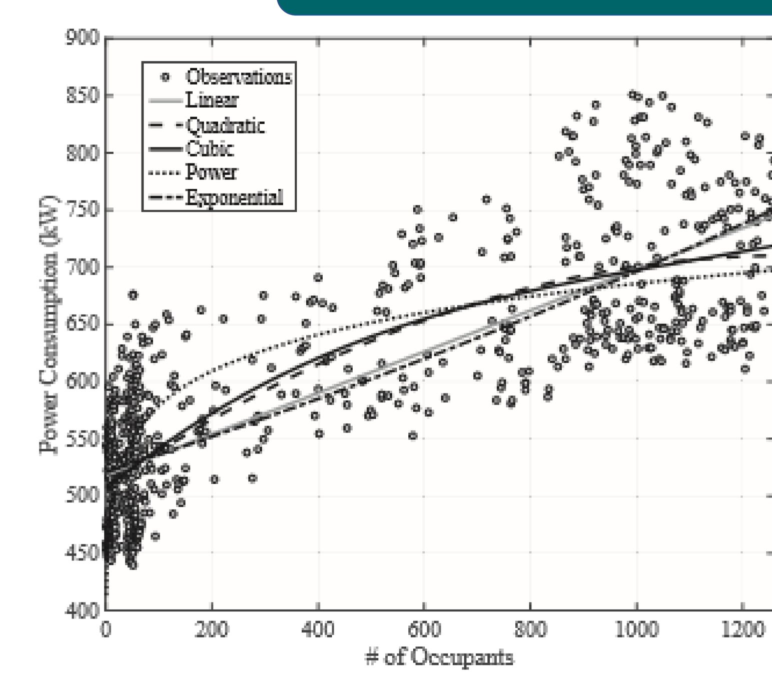
Cross-Validation: $\widetilde{M^r}(R,t)$

16: Using S' to evaluate cross-validation.
17: **if** Average cross-validation is reasonable **then**
18: $\quad$ **return** $\widetilde{M^r}(R,t)$.
19: **else**
20: $\quad R \leftarrow S$;
21: $\quad f_h(R, CM_m, \nu)$
22: **end if**

The heuristic regression algorithm builds models based on:

$$\widetilde{M^r}(x,t) = \sum_{b=1}^{q} c_b(x) \cdot \widetilde{M^r_b}(x,t), \quad c_b(x) = \begin{cases} 1 & \text{if } x \in R_b, \\ 0 & \text{if } x \notin R_b \end{cases}$$

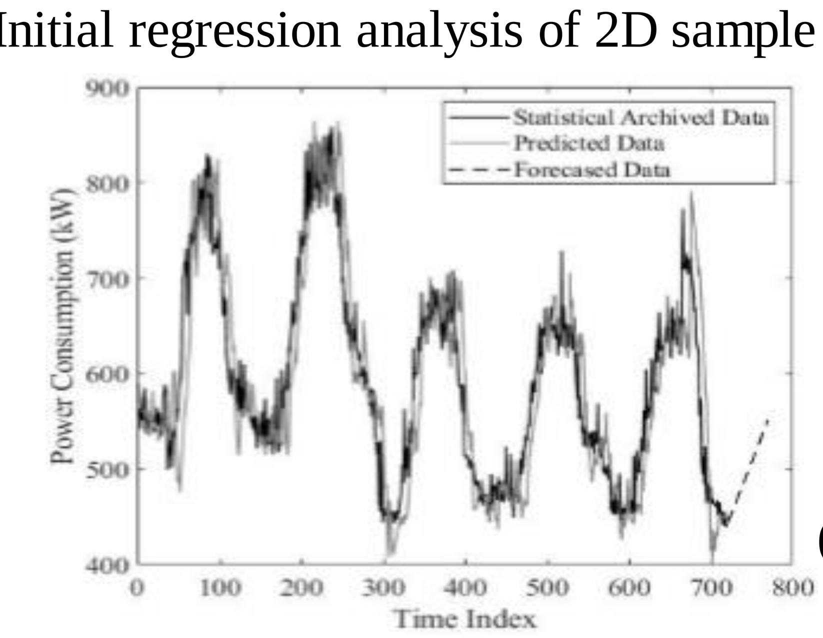
4 Case Studies



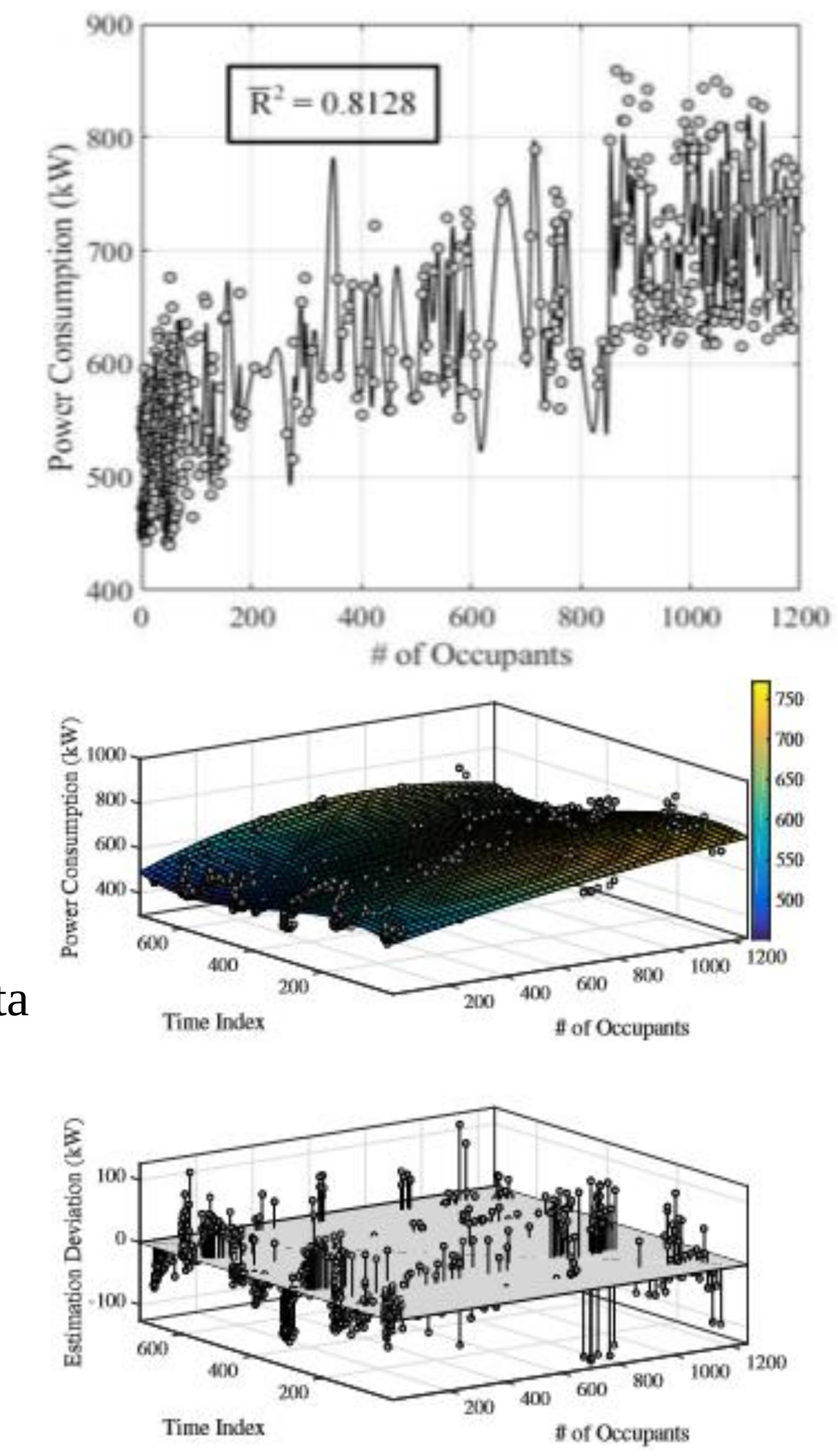
SAMPLE DATA OF INITIAL VALIDATION SUMMARY OF TEST LUMPED LOADS.

Model	R-squared	F	Sig.	GEH
Linear	0.661	52.927	0	1.762
Quadratic	0.678	63.736	0	1.323
Cubic	0.679	59.458	0	1.158
Power	0.641	81.767	0	2.309
Exponential	0.652	53.369	0	1.614

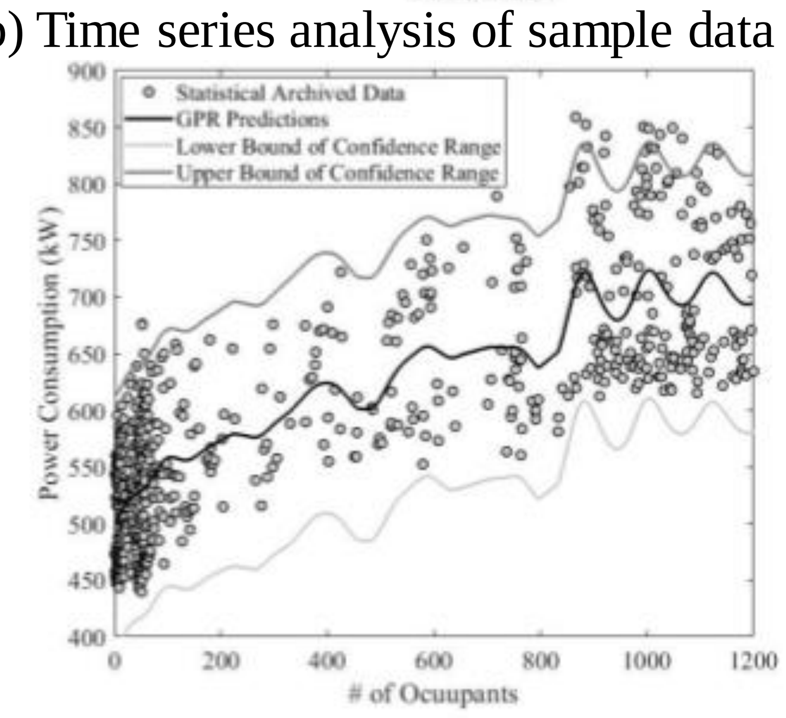
(a) Initial regression analysis of 2D sample data



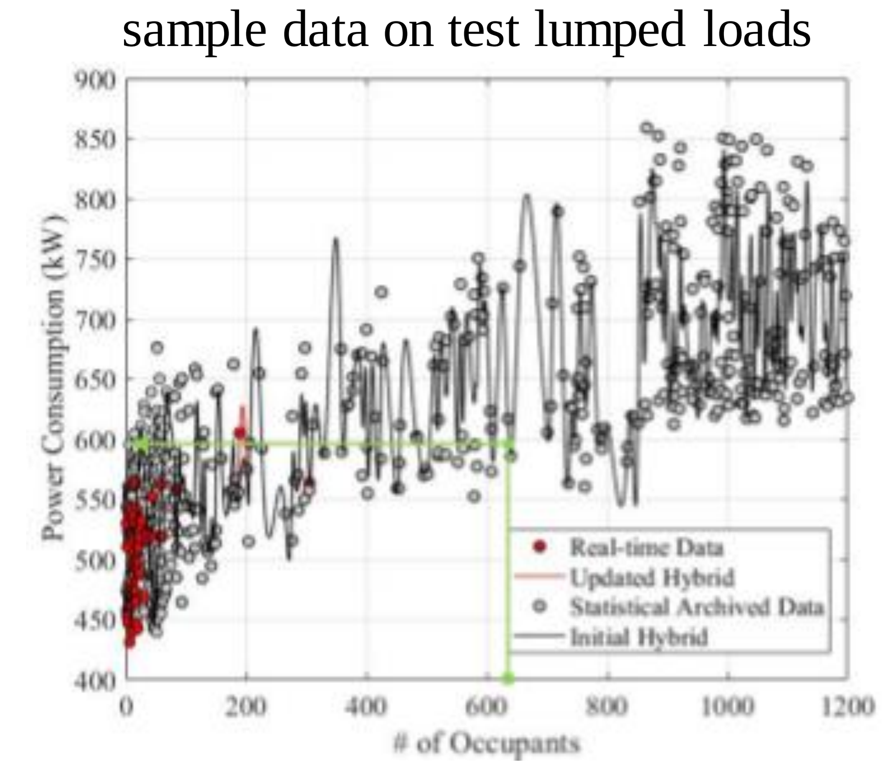
(b) Time series analysis of sample data



(d) Heuristic regression analysis of 2-D and 3-D sample data on test lumped loads



(c) GPR analysis of sample data



(e) On-going training hybrid regression model

ERROR RATE ANALYSIS OF THE TEST LUMPED LOADS IN A CONCENTRATED INTERVAL.

Name	OCC. (#)	Time Index	Power Consumption (kW)	Error Rate (%)
Metered	629	49	566.9	-
2D-Hybrid	629	49	581.809	2.63
3D-Model	629	49	578.011	1.96
ARMA	629	49	548.79	3.19
GPR	629	49	621.36	9.6

⋆ OCC. represents the number of occupants.

6 Conclusion

- The proposed finite mixtures of regression models for load model are adjusted by correlating with data available from smart meters, on-site reading, derivation of billing kWh information, or analog and binary measurements.
- The estimated occupancy can be gathered from cellular devices.
- Such correlation with human movement would strengthen the load modeling in high-regularity load such as industrial, commercial, and academic load.

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Published in IEEE Transactions on Smart Grid, 2019 (early access)

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