Using Machine Learning to Predict Occupant Hot Water Use and Improve HPWH COP

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ACEEE Hot Water Forum

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Acknowledgements

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- Funded through California Energy Commission GFO-17-304
- Applied research and technology deployment
- Creating an "Energy Marketplace" to deploy technologies

Introduction - Fundamentals

- Heat pump (HP) Coefficient of Performance(COP) > Electric Resistance (ER) COP
- HP COP = f(Water Temperature, Air Temperature)
- Time of Use (TOU) rates are coming

- Ergo, controls that…
  - Replace ER operation with HP operation,
  - Time HP use for favorable temperatures, or
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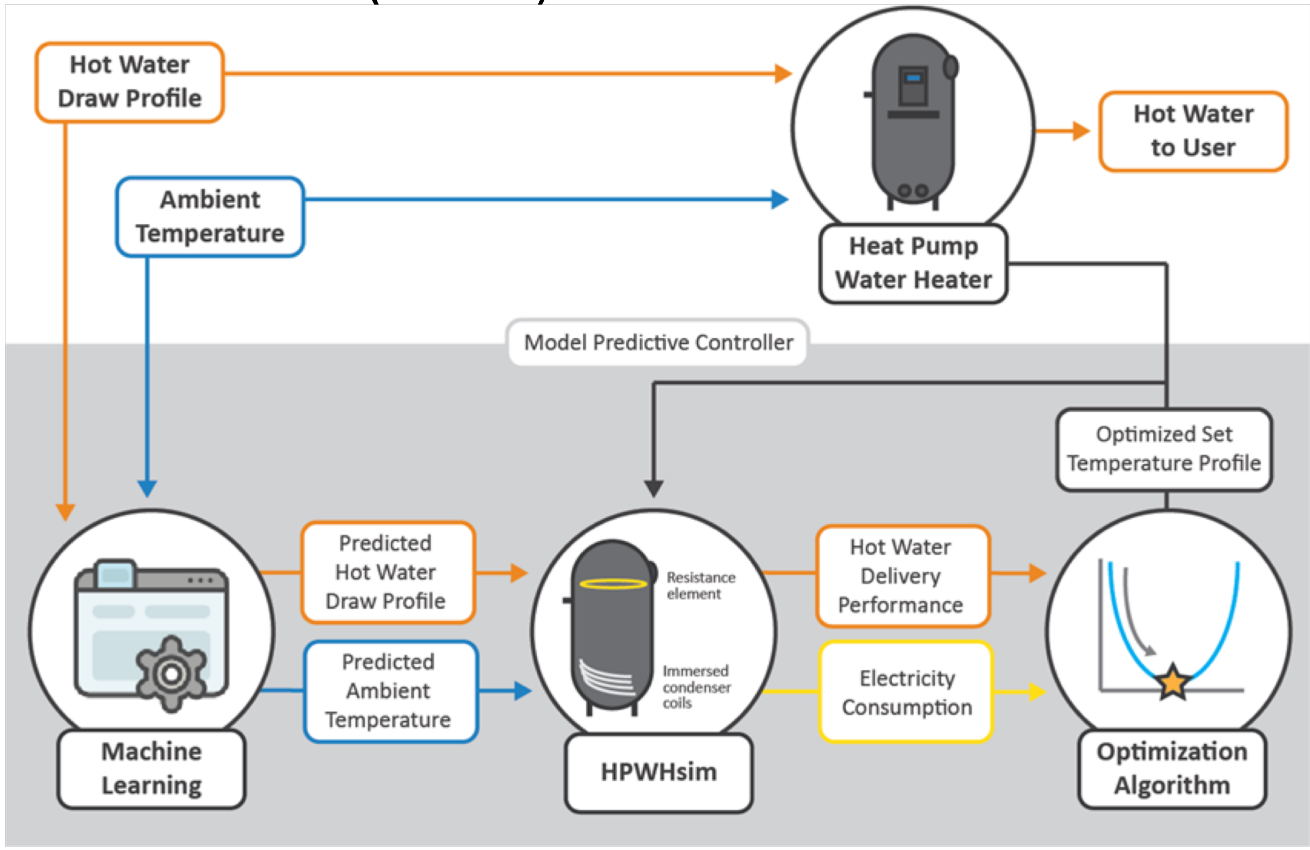

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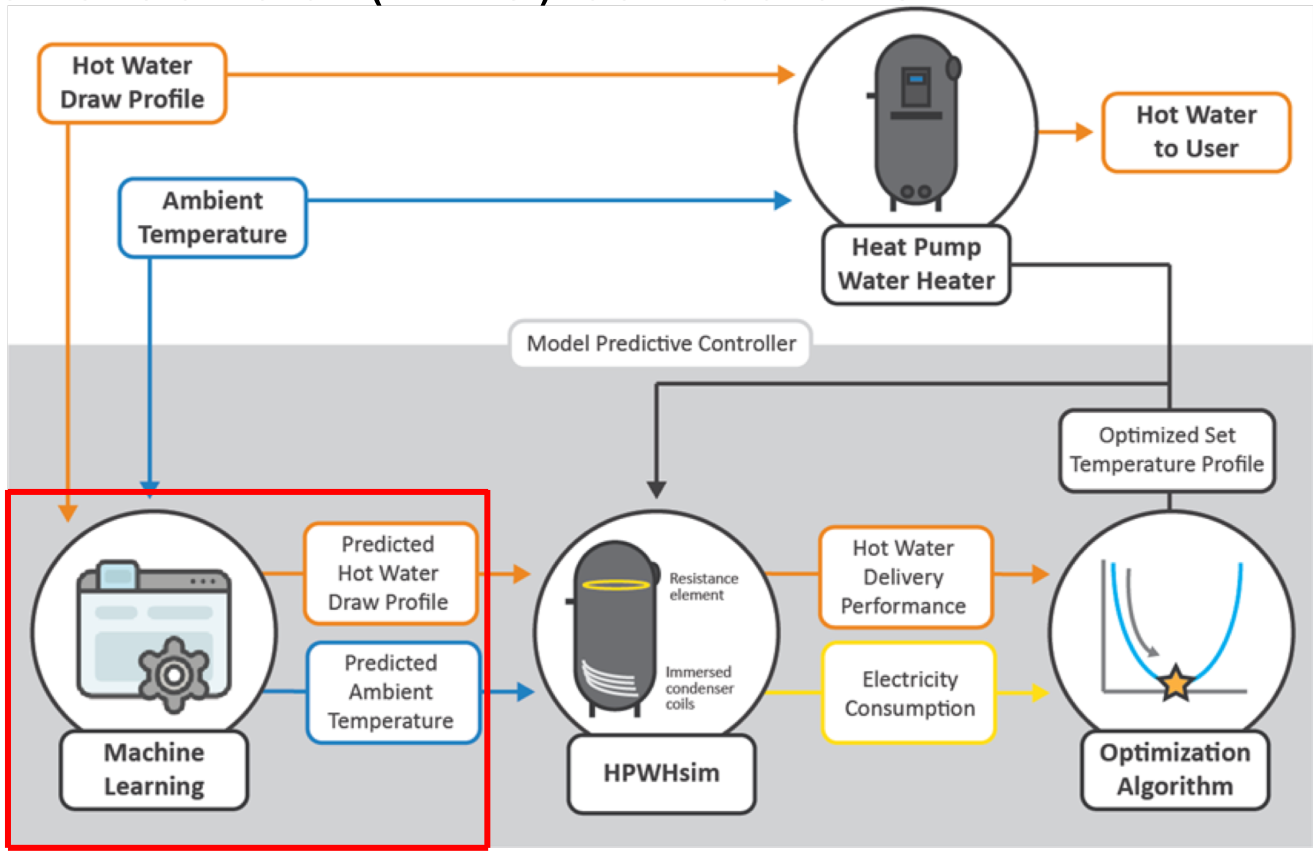


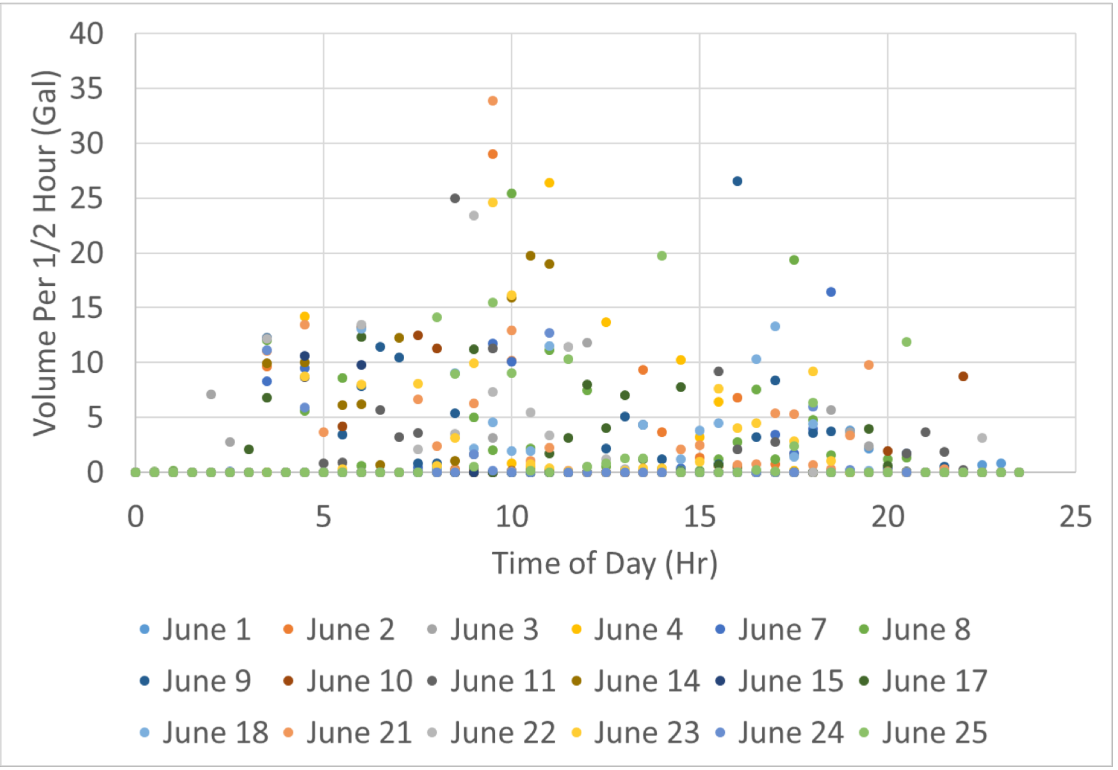
Introduction - Hypothesis

- Broad predictions of hot water draw profiles are impossible
  - Entirely too much variation between homes
- But…maybe individual occupants are fairly repeatable
  - Monitor how ***a specific household*** uses hot water
  - Develop understanding of common patterns
  - Reasonably predict future hot water use

Methods – Machine Learning Algorithms

- Use monitored data from 18 different sites
- Apply 3 machine learning techniques
  - Averaging bin
  - Averaging bin, last x days
  - ~~Template matching~~
- Compare results:
  - Run time
  - Mean bias error (MBE)
  - Root mean square error (RMSE)
  - Visual comparison

Methods – Averaging Bin



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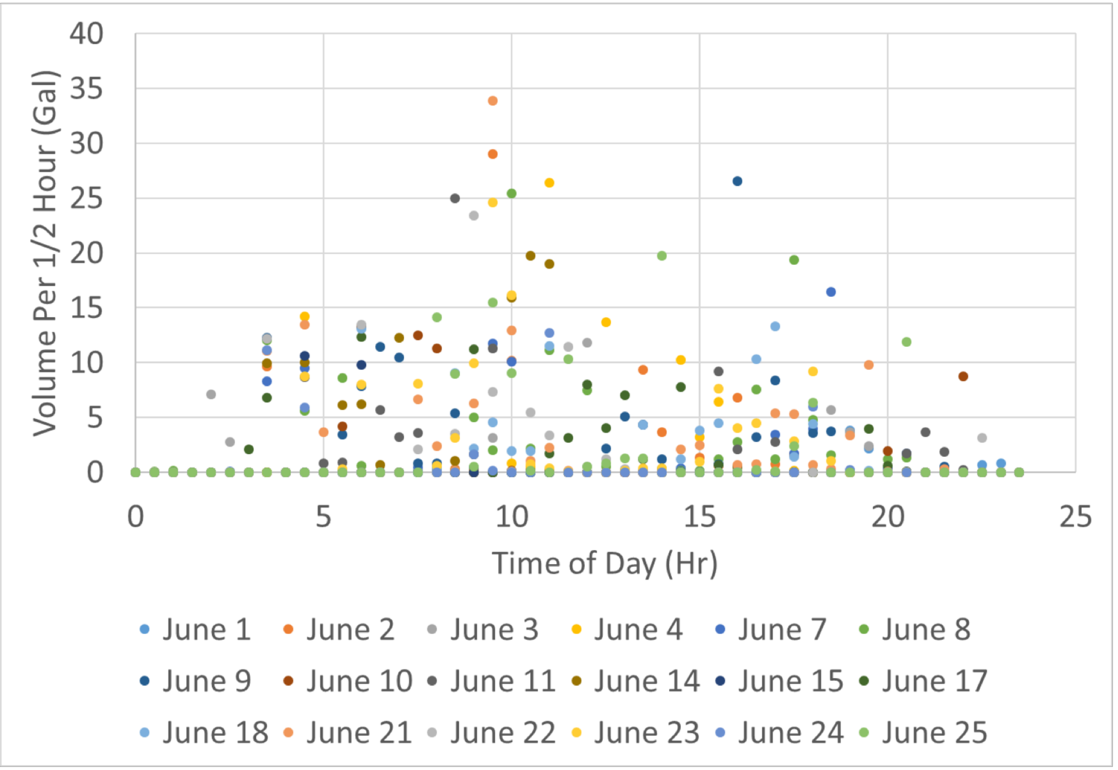
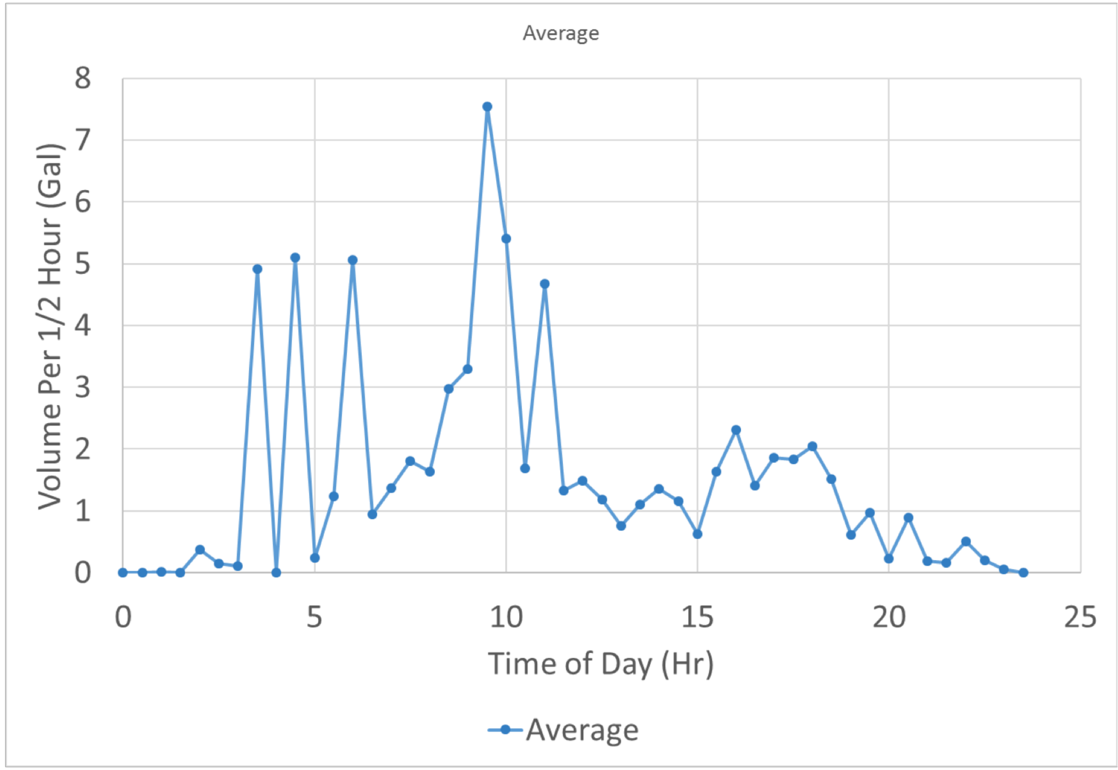
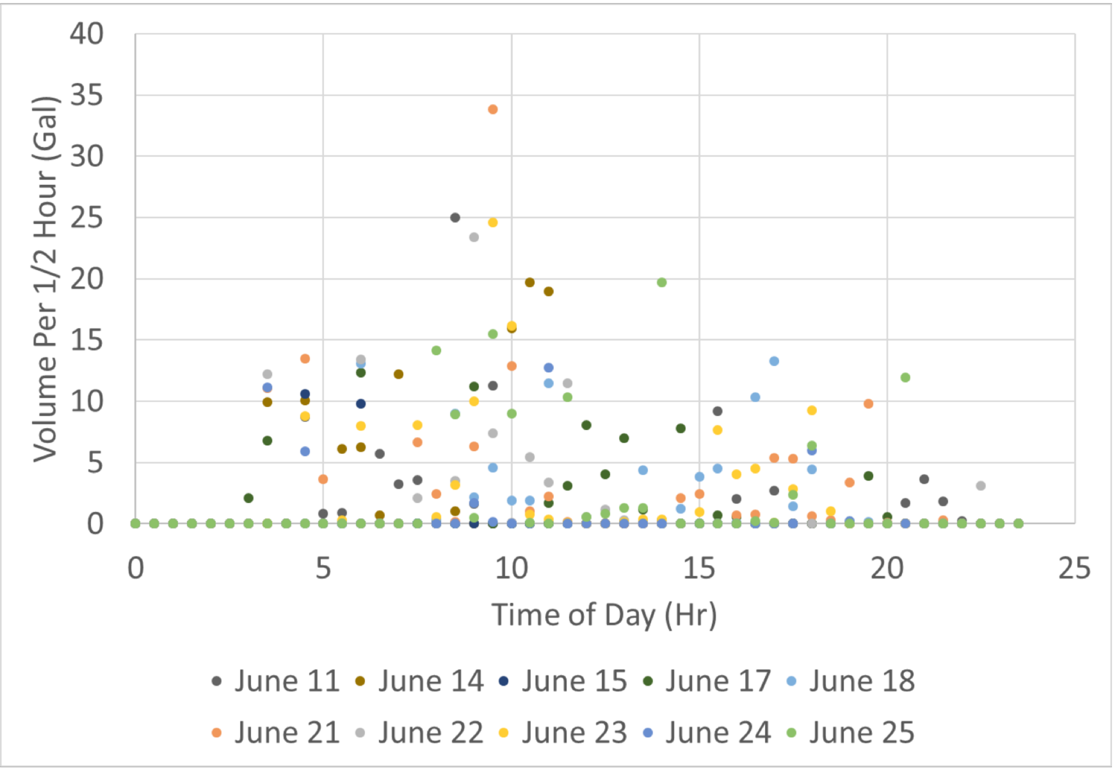
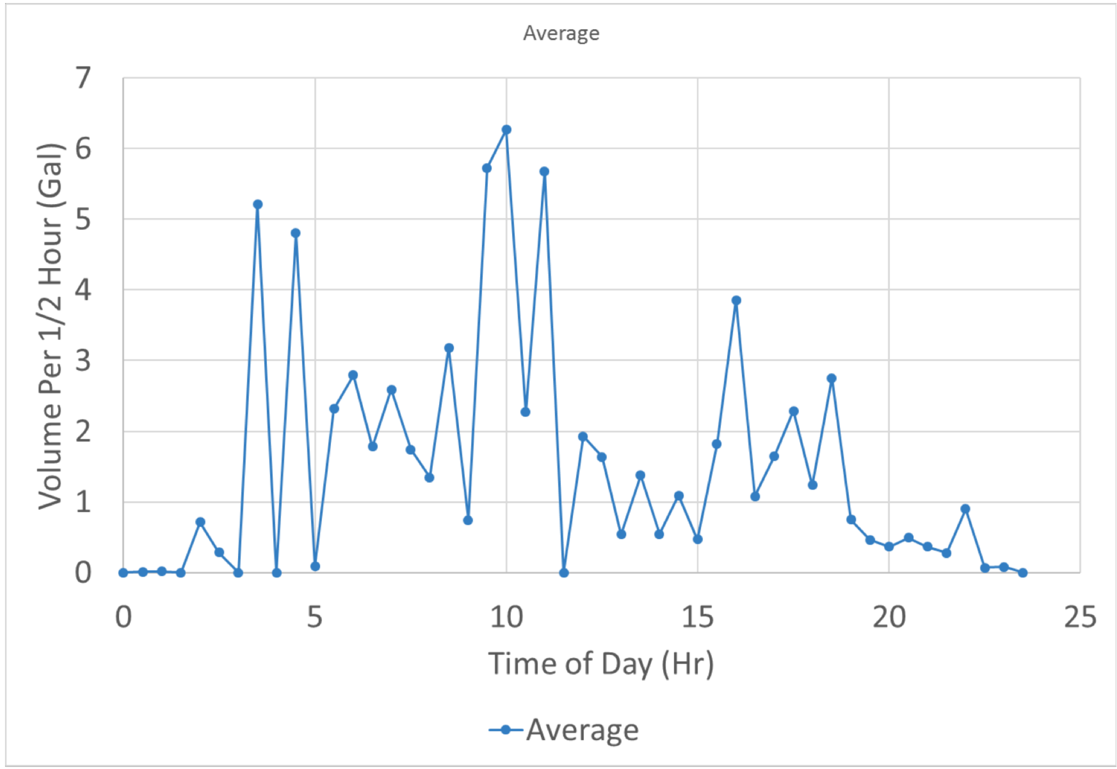




Methods – Averaging Bin, Last x Days





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Results – Calculation Time

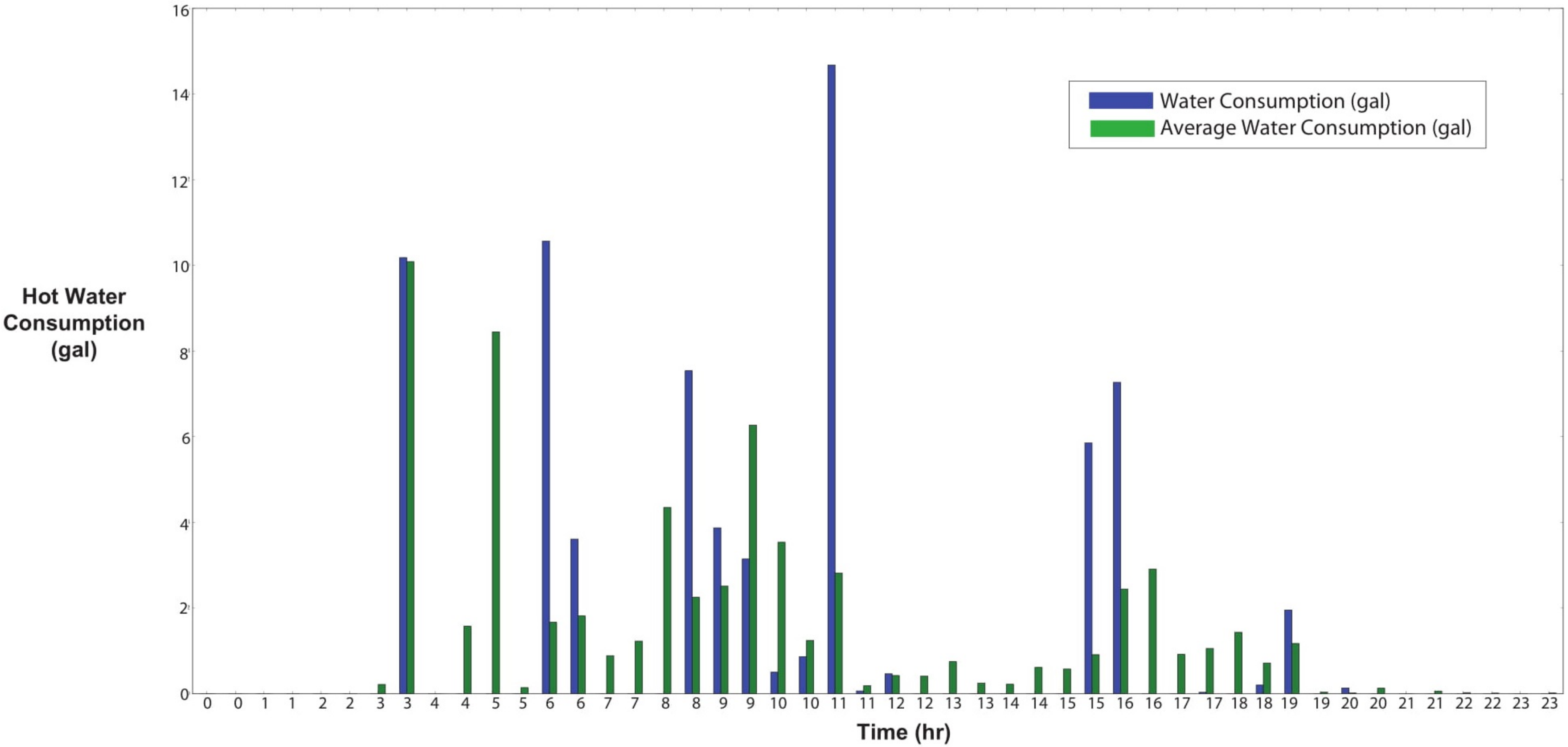
Method	Time (s)
Averaging Bin	320
Averaging Bin, Last 10 Days	299
~~Template Matching~~	~~18,780*~~

- *And it overwhelms my computer

Results - Statistics

Method	Bin Duration (Minutes)	Average Normalized Mean Bias Error (gal)	Average Root Mean Square Error (gal)
Averaging Bin	15	0.937	2.145
Averaging Bin	30	0.937	3.492
Averaging Bin	60	0.937	5.45
Averaging Bin, Last 10 Days	15	0.924	1.444
Averaging Bin, Last 10 Days	30	0.924	2.350
Averaging Bin, Last 10 Days	60	0.924	3.679

Results – Good Match



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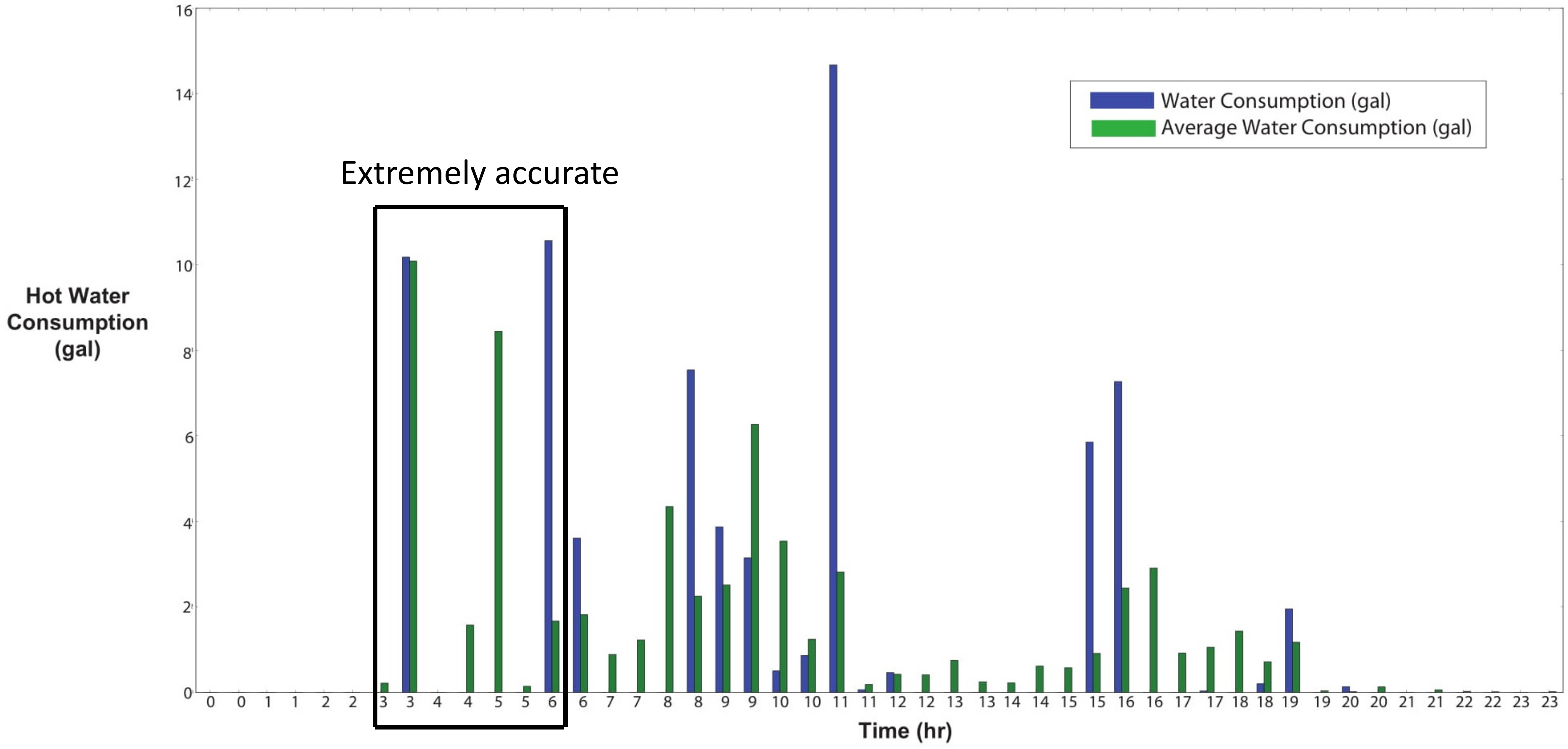

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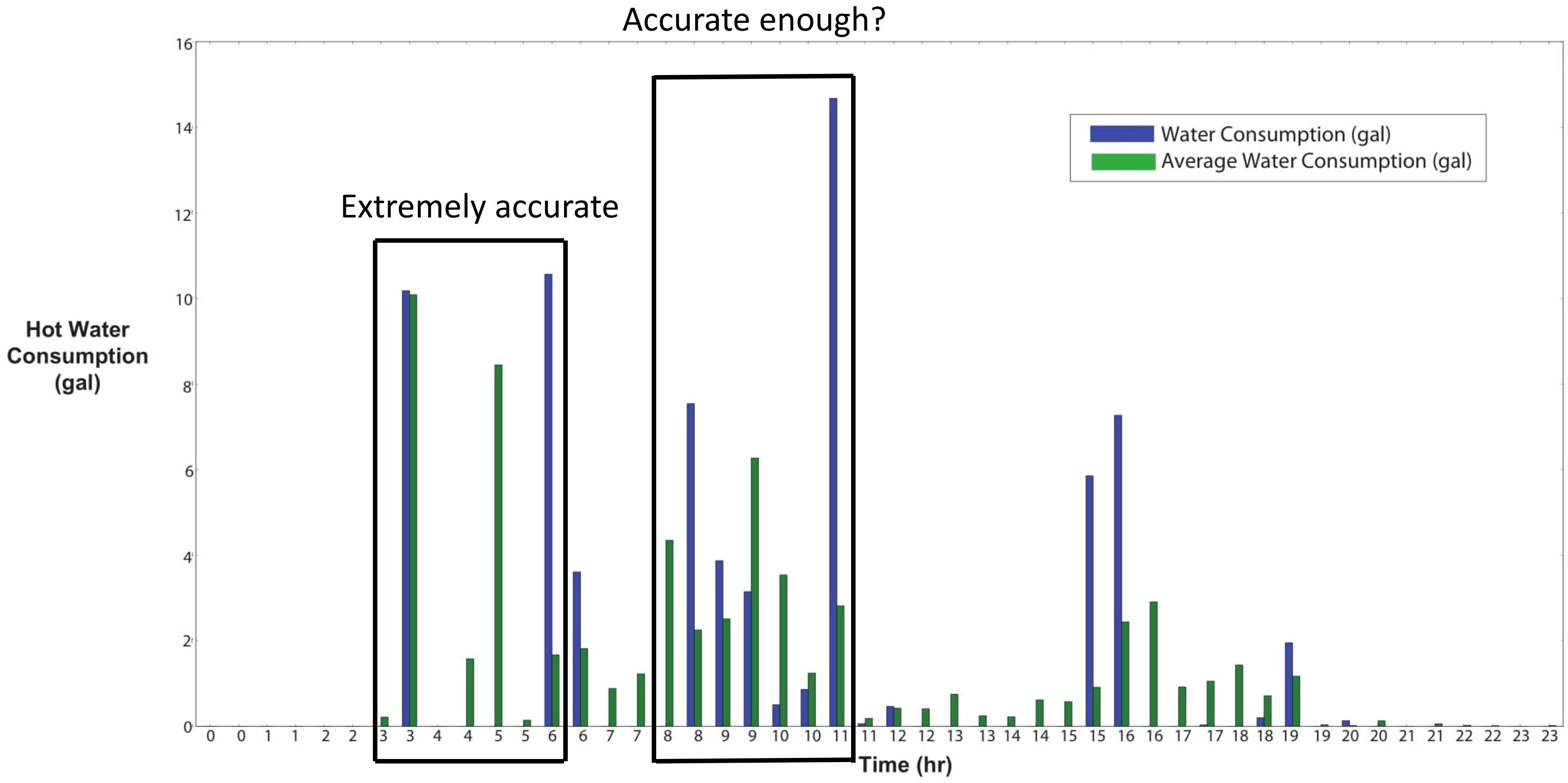

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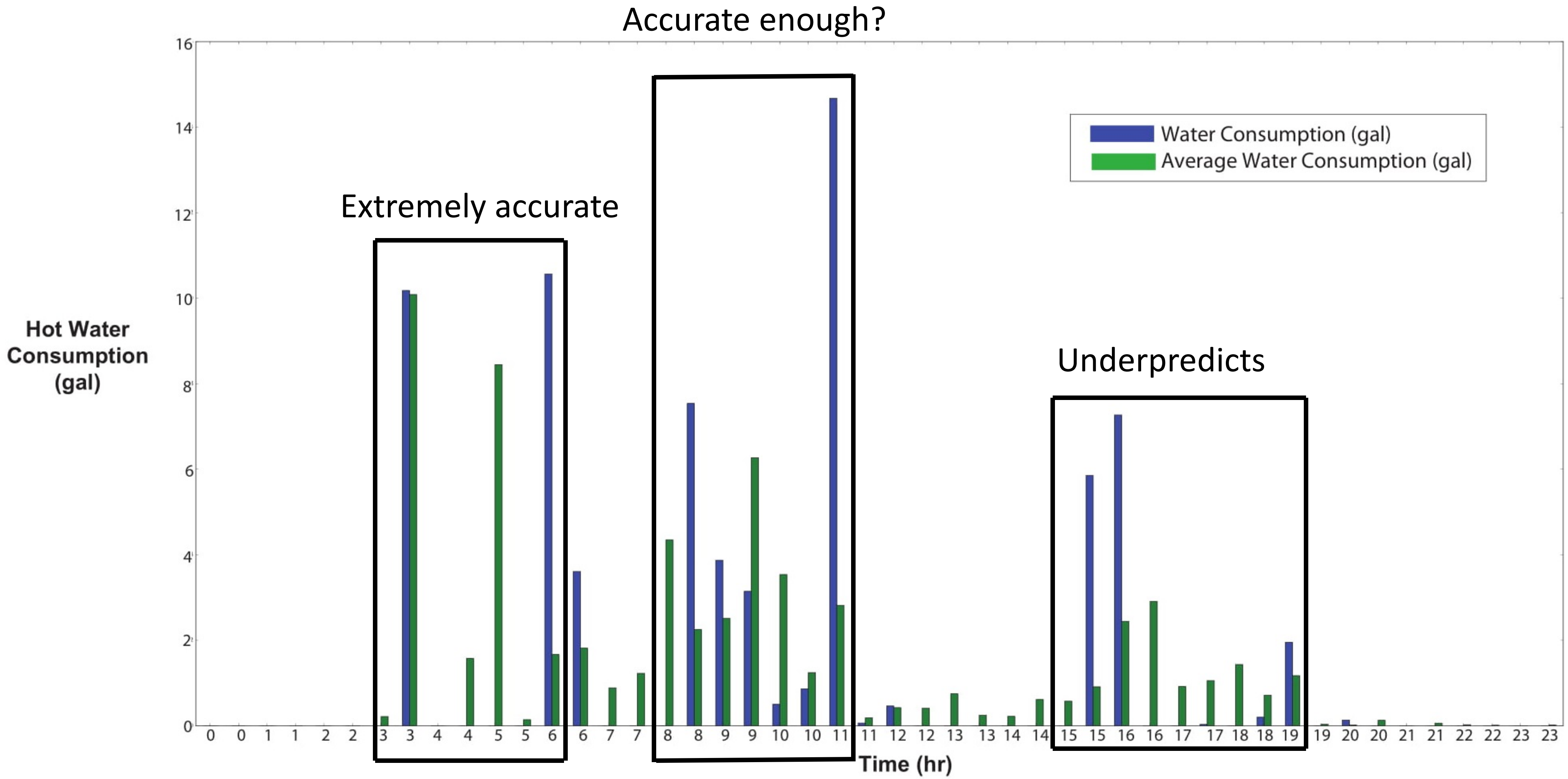

Next Steps

- Best Performer: Averaging Bin, Last 10 days, 15 min bins
- Statistics and plots show potential
- But…is it good enough?
- Use it to drive simulation and testing study
  - Predicted profile => Input to MPC
  - Actual profile => Input to simulation/test
  - ***Does it reduce occupant electricity cost?***


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