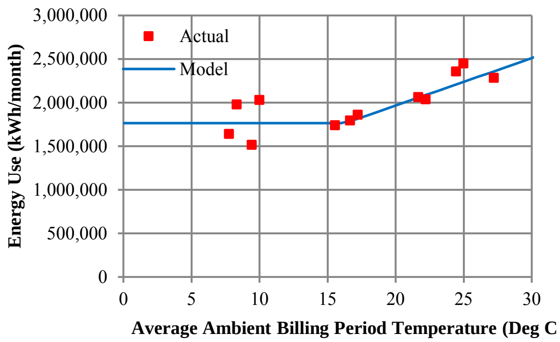

Figure 5. Actual Energy Usage vs 3PC Model Prediction for Facility B

DiscussionThis preliminary study has compared GP models to 3PC models using utility bill data and ambient dry bulb temperature. Both models have advantages and disadvantages. GP models are able to capture non-linearity better than 3PC models, however as mentioned previously, due to limited training data, initial guesses for the hyperparameters need to be accurate or poor results may be found. An advantage of the 3PC model is it has a defined equation whereas the GP model is only defined by the covariance matrix and mean function. Table 4 shows the CV-RMSE of the GP and 3PC models for both cases. In both cases the GP models had slighlty better CV-RMSE values but both models meet ASHRAE Guideline 14 requirements.

Table 4: CV-RMSE Comparison Between GP and 3PC Models for Case A and Case B

	GAUSSIAN	3PC
CASE A	12.1%	14.9%
CASE B	7.4%	8.18%

Table 5 shows the NMBE values for the GP and 3PC models in both cases. In Case A the GP model NMBE value indicates that it is the better fit. In Case B the 3PC NMBE value indicates a better fit.

Table 5: NMBE Comparison Between GP and 3PC Models for Case A and Case B

	GAUSSIAN	3PC
CASE A	0.026%	0.169%
CASE B	0.012%	0.0038%

The biggest challenge to creating accurate baseline energy models in industrial facilities is limited data availability (i.e., only 12 month utility bills are available). Due to most industrial facilities not being able to sub-meter systems, utility bill data is the only consistently-available source of information for energy usage in a facility. To make results more accurate, multiple years of utility bills can be used, but care must be exercised to ensure that the facility has not made major changes in equipment or amount of production.

CONCLUSION

This paper has presented two case studies comparing GP models to 3 parameter cooling change-point models to develop a baseline energy model using ambient dry bulb temperature and utility bill data. In both cases the both models meet the recommended measures of goodness recommend by ASHRAE Guideline 14. The CV-RMSE values indicate a better fit by the GP models, but the NMBE values show for Case A the GP model is the better fit while for Case B the 3PC model is the better fit.

For this case study, the baseline model could be any of two models although the model prediction uncertainty is intrinsically better captured in the GP model. In general, the prediction associated with uncertainty is helpful for the risk management in the retrofit project, although this preliminary study didn't research whether the uncertainties are accurately captured with GP model. This will be further investigated in the future. In addition, the Gaussian approach leads to highly flexible models, which can easily capture the complex behavior and provide more realistic results. This preliminary case study was limited to two industry facilities with total electricity consumption data in southeastern regions, the conclusions drawn from this preliminary study may not be fully representative, generalizable conclusion. However, the flexible framework used in this study can be easily adapted into any other case studies including different locations, different input and out variables, etc.

Future goals are to perform an in depth comparison of GP models to change-point temperature models, to analyze various covariance matrices, to analyze hyperparamters for connections to building material properties or infiltration and to use the models to help break down energy usage (i.e. air conditioning usage, motors, lighting, etc.) in the industrial facilities. Additional future work will focus on expanding the application of GP model to more industrial facilities, under different use scenarios and comparing their performance in different time resolution.

NOMECLATURE

η = hyperparameters

X = ambient dry bulb temperature

V(X,X, η) = covariance matrix

y = energy usage

m(x) = mean function

E = energy usage

β_1 = weather independent energy usage

β_1 = weather dependent energy usage

T_{amb} = ambient temperature

$T_{b,c}$ = change-point temperature

y_{act} = actual energy usage

y_{mod} = model energy usage

y_{act_bar} = average actual energy usage

n = number of data points

p = number of parameters

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