CONCLUSIONS

This paper shows that a surrogate model for a building can be highly accurate for a range of locations with varying climates. These models are generally five orders of magnitude faster at predicting the energy consumption than a detailed EnergyPlus simulation, which makes design optimization and immediate feedback possible in building design. In this paper, only a single climate variable, heating degree days, was included in the model. Future work will explore other parameters that can describe weather including cooling degree days, humidity levels and solar radiation. Even further, we plan to expand the surrogate model for multiple building types and include variables for building size and shape into the surrogate model.

NOMENCLATURE

$s(x)$	Radial basis function prediction solution
w_i	Radial basis function weight
$\boldsymbol{c}_i$	Basis function centers
$\boldsymbol{x}$	Prediction site
r	$\lVert\boldsymbol{x}-\boldsymbol{c}_i\rVert$ normalized prediction site
σ	Parametric radial basis function parameter
θ	Kriging basis
p	Kriging exponent
ϕ_q	Annual heat flower per unit area
dS	Surface differential
U	Surface U-Factor
A	Surface area
ΔT	Temperature difference
dt	Time differential
(x_i, y_i)	Data pairs
$\bar{x}$	Mean value

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