Results and Challenges in the Use of Predictions to Manage Building Operations

Francesco Borrelli
Email: fborrelli@me.berkeley.edu
Department of Mechanical Engineering
University of California
Berkeley, USA
www.mpc.berkeley.edu
Can We Make Buildings Greener?
(Using Models and Forecasts)

Humans → Predictive Controller → Building

Predictions on
Building Dynamics, Weather, Occupancy, Comfort
Basic Idea

\[ y(k + 1) = y(k) + b_w w(k) + b_u u(k), \quad y(k) \in \mathcal{Y}(k) \]

At step \( t \) decide on \( u(t) \) based on prediction on \( w(t),..., w(t+N), \mathcal{H}(t),...,\mathcal{H}(t+N) \)

Two Combined Effects: Anticipation and Coordination
Steps Towards Success

- **human, environment** constraints
- **control action**

\[ y(k + 1) = y(k) + b_w w(k) + b_u u(k), \quad y(k) \in \mathcal{Y}(k) \]

At step t decide on u(t) based on prediction on w(t),..., w(t+N), \mathcal{Y}(t),...,\mathcal{Y}(t+N)

- “Good” Model Abstraction
- Quantifying Uncertain Predictions
  \[ w(t + 1|t) \in \mathcal{W}(t + 1|t), \ldots, w(t + N|t) \in \mathcal{W}(t + N|t) \]
- Predictive Control Design
Steps Towards Success

\[ y(k+1) = y(k) + b_w w(k) + b_u u(k), \quad y(k) \in \mathcal{Y}(k) \]

At step \( t \) decide on \( u(t) \) based on prediction on \( w(t), \ldots, w(t+N), \mathcal{Y}(t), \ldots, \mathcal{Y}(t+N) \)

- “Good” Model Abstraction
- Quantifying Uncertain Predictions
  \[ w(t + 1|t) \in \mathcal{W}(t + 1|t), \ldots, w(t + N|t) \in \mathcal{W}(t + N|t) \]
- Predictive Control Design
Models of... (different systems and abstraction)

Models with..
System Description: Cooling System

Chillers and Cooling towers

Tank

controller

controller

controller

Pumps
System Description: Cooling System

- Chillers and Cooling towers
- Tank
- Controller
- Pumps

www.mpc.berkeley.edu

Borrelli (UC Berkeley)
System Description: Cooling System

**AHU** (air handler unit) cooling coils and supply fan

**VAV** (variable air volume box) heating coil and damper

Pumps

Chillers and Cooling towers

controller
**System Description: Cooling System**

- **Typical in New Constructions**
  - Variable Air Volume with reheat

- **Control Inputs**
  - Supply fan, cooling coil, heating coils, zone dampers, air handling unit dampers

---


System Abstraction
Lumped, Reduced-Order, Data-Driven

Dynamics:
Bilinear Differential Equations
  - RC thermal zone model

Components:
Static Nonlinearities
  - Chillers, Cooling Tower
  - Fan
  - Cooling and heating coils
“Thermal zone,” arbitrary lumped control volume:

\[ \dot{Q} \]

supply air \( T_s \)  
mass flow rate \( m_s \)  
lumped state \( T_z \)  
well-mixed exit air \( T_z \)  
exit flow rate = supply flow rate \( m_s \)

First-order energy balance, temperature dynamics:

\[ (mc) \frac{d}{dt} T_z = \dot{Q} + c_p m_s (T_s - T_z) \]

zone thermal capacitance  
heat capacity of air
\[ C_1^i \dot{T}_1^i = m_s^i c_p (T_s - T_1^i) - \frac{T_{oa} - T_1^i}{R_{oa}^i} + \frac{T_2^i - T_1^i}{R^i} + P_d^i + \sum_{k \in N^i} \frac{T_{1,1}^i - T_1^i}{R_k^i} \]

\[ C_2^i \dot{T}_2^i = \frac{T_1^i - T_2^i}{R^i} \]

\[ T_s = \delta T_r + (1 - \delta) T_{oa} - \Delta T_c + \Delta T_h^i \]
Polynomial Component Models

- Centrifugal Chiller Model Power Consumption Model:
  - Chiller water supply temperature
  - Condenser water supply temperature
  - Capacity

- Fan power: \( P_f = c_0 + c_1 \text{in}_s + c_2 \text{in}_s^2 \)

- Cooling and heating coil: simplified as a static energy converter

Average error of 1.48%
Steps Towards Success

Human, environment constraints

\[ y(k + 1) = y(k) + b_w w(k) + b_u u(k), \quad y(k) \in Y(k) \]

At step \( t \) decide on \( u(t) \) based on prediction on \( w(t), \ldots, w(t+N), Y(t), \ldots, Y(t+N) \)

- Good Model Abstraction
- Quantifying Uncertain Predictions
  \[ w(t + 1|t) \in \mathcal{W}(t + 1|t), \ldots, w(t + N|t) \in \mathcal{W}(t + N|t) \]
- Predictive Control Design
Berkeley Temperature Forecasts, Nov 2011

Prediction horizon [days] - Sampling 3hrs

UC Merced - Load Demand October 2011
Data-Driven, Learned, Load Uncertainty

Min and max difference between the measured data and the prediction model.

MPC workshop 2011
Dynamic Coupling Graph

Zone temperature may be affected by another VAV box - via open doors, missing walls etc...
Ex.: zones 4 and 15.

Correlation: PowerIn vs Zone temperature
Simplest Useful Model Abstraction

Network of Bilinear Systems

\[ \begin{align*}
\dot{Q} &= T_s \\
\dot{T}_s &= T_z \\
\dot{T}_z &= \dot{m}_s \\
\end{align*} \]

\( \text{Thermal zone model} \)

\[
(mc) \frac{d}{dt} T_z = \dot{Q} + c_p \dot{m}_s (T_s - T_z)
\]

Static Nonlinearities

- Equipment Performance Maps (Chillers, Cooling tower, Pumps, Fan, Coils)

Equality and inequality Constraints

- Comfort range
- Dynamic coupling: thermal, supply air & return air

Uncertain Predictions

- Load (Occupancy/Thermal Comfort, Sun radiation, weather)
Steps Towards Success

\[ y(k + 1) = y(k) + b_w w(k) + b_u u(k), \quad y(k) \in \mathcal{Y}(k) \]

At step \( t \) decide on \( u(t) \) based on prediction on \( w(t), \ldots, w(t+N), \mathcal{Y}(t), \ldots, \mathcal{Y}(t+N) \)

- Good Model Abstraction
- Quantifying Uncertain Predictions
  \[ w(t + 1|t) \in \mathcal{W}(t + 1|t), \ldots, w(t + N|t) \in \mathcal{W}(t + N|t) \]
- Predictive Control Design
At time $t$:

- Measure (or estimate) the current state $x(t)$.
- Find the optimal input sequence.
- Apply only $u(t) = u^*(t)$, and discard $u^*(t+1), u^*(t+2), \ldots$

Repeat the same procedure at time $t+1$.
Model Predictive Control (MPC)

Advantages:
• Predictive
• Systematic: no if-then-else and extensive trial and error tuning
• Multivariable, Model Based
• Guarantees: Performance and Constraint satisfaction
• Large success in the process industry
• Flexible/ Easy to Integrate
Current MPC Lab Research

- Abstraction Models
- Role of Prediction Errors
- Global vs Local Optima
- Real-time Computation
  - Distributed MPC
  - Tailored MPC Solvers
- Numerical Tools for efficient Computation
- Hardware implementation and Experimental Tests
Current MPC Lab Research

- Abstraction Models
- **Role of Prediction Errors**
- Global vs Local Optima
- Real-time Computation
  - Distributed MPC
  - Tailored MPC Solvers
- Numerical Tools for efficient Computation
- Hardware implementation and Experimental Tests
Predictive Control Design for Large Scale Systems
Computational Tractability and Reduced Conservatism

\[
\min_{\pi_0(\cdot), \pi_1(\cdot), \ldots, \pi_{N-1}(\cdot)} J_{0 \rightarrow N}(x_0, \Pi)
\]
subj. to
\[
k = 0, \ldots, N - 1 \left\{ \begin{array}{l}
x_{k+1} = f(x_k, u_k, w_k) \\
u_k = \pi_k(x_k) \\
u_k \in \mathcal{U}, x_k \in \mathcal{X}, \quad \forall w_k \in \mathcal{W}
\end{array} \right.
\]

- Select class feedback control policies \( \pi_k() \)

\[
\pi_k : x_k \in \mathcal{X} \mapsto u_k \in \mathcal{U}
\]

- Relax the constraint satisfaction

\[
\Pr \left\{ \bigcup_{k=1}^{N} x_k \not\in \mathcal{X} \right\} \leq \epsilon, \quad \forall w_k \in \mathcal{W}
\]

- Exploit structure of resulting optimization problem
Fast Stochastic Predictive Control for Bilinear Networked Systems

\[
\min_{\pi_0(\cdot), \pi_1(\cdot), \ldots, \pi_{N-1}(\cdot)} J_{0\to N}(x_0, \Pi)
\]

\[
\text{subj. to } k = 0, \ldots, N - 1 \quad \begin{cases} 
  x_{k+1} = f(x_k, u_k, w_k) \\
  u_k = \pi_k(x_k) \\
  u_k \in \mathcal{U}, x_k \in \mathcal{X}, \quad \forall w_k \in \mathcal{W},
\end{cases}
\]

- Select class feedback control policies \(\pi_k(\cdot)\)
  Partial Closed-Loop

- Relax the constraint satisfaction
  Explicit Chance Constraint

- Exploit Structure of Resulting Optimization Problem
  SQP and exploit the sparsity of the linearized problem
  - Centralized, Primal-Dual Interior Point Algorithm
  - Distributed, Lagrangian Decomposition + Fast Gradient Method
DOE library Model

\[ \begin{align*}
T_{k-1}^k &= \text{Zone}(T_{oa}^k, T_{oa}^{k-1}, T_{oa}^{k-2}, (T_s^k - T^k) \hat{m}^k, T_s^k \hat{m}^k, I^k, I^{k-1}, I^{k-2}, T_s^k, T_s^{k-1}, T_s^{k-2}) \\
T_{oa} &\quad \text{ambient temperature} \\
T_s &\quad \text{supply air temperature} \\
\hat{m} &\quad \text{supply air flow rate} \\
I &\quad \text{solar radiation intensity}
\end{align*} \]

Historical ambient temperature

Historical solar load

Historical occupancy load
Stochastic MPC for DOE library

---

**Zone temperature:** dashed lines
**Zone constraints:** solid lines

**Solid lines:** stochastic MPC

**Dashed lines:** Baseline control

---

SMPC achieved 22% energy savings while maintaining the same level of comfort violations as baseline control (BC) (5%)
Stochastic MPC for DOE library

Dashed lines: Baseline control
Solid lines: stochastic MPC

SMPC consumed 1.6% more energy while allowing 5% of comfort violations. BC violates the comfort constraints with a chances of 12%.
Current MPC Lab Research

- Abstraction Models
- Role of Prediction Errors
- Global vs Local Optima
- Real-time Computation
  - Distributed MPC
  - Tailored MPC Solvers
- Numerical Tools for efficient Computation
- Hardware implementation and Experimental Tests
Centralized Model Predictive Control

\[
\min_{U} \sum_{k=t}^{t+N-1} l(x_k, u_k)
\]

subj. to
\[
\begin{align*}
x_{k+1} &= f(x_k, u_k), \; k = t, \ldots, t + N - 1 \\
u_k &\in U, \; k = t, \ldots, t + N - 1 \\
x_k &\in \mathcal{X}, \; k = t, \ldots, t + N - 1 \\
x_t &= x(t)
\end{align*}
\]

Five thermal zones and 24 prediction steps
312 optimization variables, 1272 constraints
IPOPT spends one hour to solve on standard PCs
What is BLOM?

- A language of modeling dynamical nonlinear systems for optimization problems, especially MPC.
- Support for the following design phases:
  - Developing the model with an intuitive block diagram.
  - Forward simulation and validation of the model.
  - Automatic export of the optimization problem to a solver.
- Developed to handle non trivial problems
  - C++ or Matlab code generation.
  - Explicit evaluation of Jacobian and Hessian.
  - Proven with problems of tens of thousands variables.
- Eliminates manual problem coding, eases maintenance and assures that the same model used for optimization and for simulation.
- Create model using Simulink with BLOM library. Run and compare the model to a reference data.
- Translate to optimization problem: `ExtractModel(steps,dt,’RK4’);`
- Export the problem to a solver: e.g. `CreateIpoptCPP`

- Used to create MPC controller for a large HVAC system: 41 zones, 430 states, 30 time steps, 37000 variables, 40000 constraints needs <1 minute solver time with IPOPT.
Current MPC Lab Research

• Abstraction Models
• Role of Prediction Errors
• Global vs Local Optima
• Real-time Computation
  • Distributed MPC
  • Tailored MPC Solvers
• Numerical Tools for efficient Computation
• Hardware implementation and Experimental Tests
Multiple Large-Scale Experimental Tests

- **UC Merced**, Merced, CA
  
  *Ended: 4% Improvement*
  
  Storage, Chiller Optimization
  Horizon 24hrs, Sampling 30min
  Problem Size: ~300 variables, ~1440 constraints

- **CERL Engineering Research Laboratory, Champaign, IL**
  
  *Ended: 15% improvement.*
  
  HVAC distribution – 5 zones
  Horizon 4hrs, Sampling 20 min,
  Problem Size: ~1600 variables, ~1400 constraints

- **Naval Station Great Lakes, North Chicago, Illinois**
  
  *ONGOING: Generation+ HVAC distribution – 250 zones*
  
  Problem Size: ~20k variables, ~?? constraints

- **CITRIS Building (UC Berkeley) – Major issues**
  
  *ONGOING* Generation + HVAC distribution -135 Zones
  Horizon 4hrs, Sampling 20 min,
  Problem Size: ~10k variables, ~?? constraints

- **Brower Center (Slab Radiant), Berkeley, CA**
  
  *ONGOING: Architecture Department*
  
  Models based on step tests experiments
Conclusions

• Next Generation of Control System **has to** Embed Models and Predictions in the Control System

• **Multiple advantages:**
  • Development time
  • Savings
  • D/R
  • Automated Commissioning

• **Need tools for:**
  • Easing the process from control design to implementation
  • Fast analysis of potential improvements

• **Our Research:**
  • Modeling
  • Predictive control design
  • Tools & implementation

• More on: www.mpc.berkeley.edu
Acknowledgements

• Yudong Ma
• Tony Kelman
• Sergey Vicky
• Sara Kohler
• Frank Chuang
• Yadranko Matusko
• Allan Daly

Industrial Partners

Ford Research Labs (Dearborn, USA)
• Eric Tseng, Davor Hrovat

Honeywell Labs (Minneapolis, Vancouver, Prague)
• Datta Godbole, Greg Stewart, Jaroslav Pekar

UTRC (Hartford, USA)
• Sorin Bengea, Satish N, Clas Jacobson

Siemens Research lab (Princeton, USA)
• Yan Lu

Pirelli Research Labs (Milano, Italy)
• Giorgio Audisio, Federico Mancosu

Government Agencies

NSF
AFOSR
U.S. Department of Energy