Economic Model Predictive Control for Variable Refrigerant Systems

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Economic Model Predictive Control for Variable Refrigerant Flow Heat Recovery Systems

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ABSTRACT

Variable refrigerant flow (VRF) systems are in a unique position to be combined with economic model predictive control (MPC) in order to reap significant cost saving benefits. In buildings that are subject to variable utility pricing, it is feasible to use the building mass to shift a portion of the heating or cooling load from the high priced (peak) period to a lower priced (off-peak) period.

A non-linear optimization approach is applied to VRF heat recovery systems in order to determine the optimal heat/cooling loads and temperature setpoints over the horizon. Simulation of a commercial building shows annual heating, ventilation and air conditioning energy and cost savings of 22% and 25% (respectively).

1. INTRODUCTION

Variable refrigerant flow (VRF) systems are capable of satisfying building heating, ventilation and air conditioning (HVAC) needs under heating or cooling conditions. Typical commercial VRF systems, not only provide heating and cooling capabilities, but also the ability to simultaneously heat and cool different zones. Systems that provide for simultaneous heating and cooling of different zones are referred to as heat recovery systems. In these systems, the refrigerant is used to transport the energy (or heat) from one zone to another zone. Thus the energy efficiency under these conditions is improved as compared to separate heating and cooling equipment. In essence, a heat recovery VRF compressor performs the work necessary to simultaneously satisfy the heating and cooling needs within a building.

In Figure 1 below, a simple representation of a VRF heat recovery system is shown. The basic components include indoor units, outdoor units, and piping. The piping transports liquid and vapor phase refrigerant to and from the indoor units (depending on whether heating or cooling is required). The indoor units condense or evaporate refrigerant in order to provide the individual zone heating or cooling (respectively). Outdoor units compress refrigerant and perform either condensation or evaporation as necessary, in order to satisfy the overall energy balance.

Figure 1: Typical Installed VRF System

The purpose of this paper is to illustrate the potential savings when applying economic model predictive control (MPC) algorithm to VRF systems employing heat recovery. This paper will use simulation to show that by applying the technology to VRF systems, one can reduce HVAC costs.

2. PREVIOUS WORK

Economic MPC is a promising technology for energy cost optimization of buildings because it provides a natural framework for optimally controlling such systems to minimize the energy cost while meeting system constraints (Ma et al., (2012); Mendoza-Serrano & Chmielewski, (2012); Touretzky & Baldea, (2014); Patel et al., (2016), in press).

Previous work has established that economic MPC can be used to minimize HVAC utility costs in buildings subject to varying utility rates. Ellis and Wenzel, (2017); have described a two-step, hierarchical MPC framework designed to leverage building mass by temporally shifting HVAC loads within a variable utility pricing environment and thus providing economic savings. Based on this algorithm, temperature setpoints are delivered to individual zones for the greatest economic savings.

3. APPROACH

3.1 Model

In order to accommodate a heat recovery system, a model was developed consisting of 2 zones connected to a single VRF system. Each zone has a single VRF indoor heat exchanger unit capable of providing heat from compressed refrigerant vapor or cooling from high pressure liquid. These are connected to a single outdoor unit comprised of a compressor and a single heat exchanger. The model abstraction for each zone is represented as the thermal circuit shown in figure 2 as shown by Tapiero Bernal and Ellis (2107).

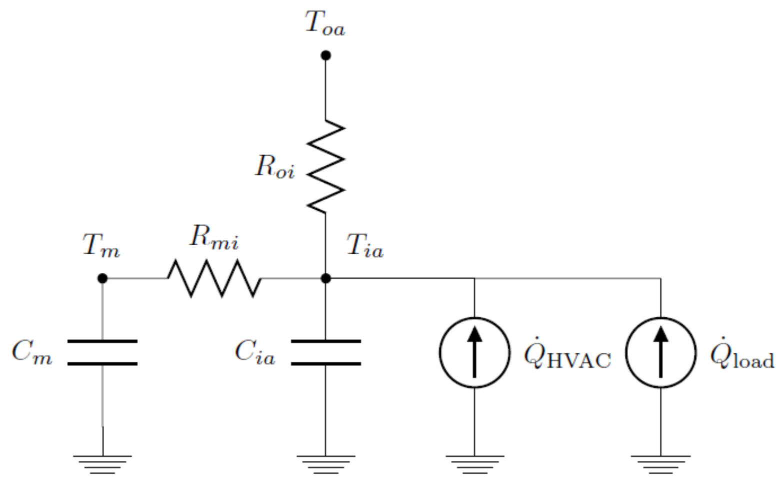

Figure 2: Circuit Representation of a Single Zone

where:

T_{ia}	– indoor air temperature.
T_{oa}	– outdoor air temperature.
T_m	– thermal mass temperature.
C_m	– lumped mass thermal capacitance.
C_{ia}	– indoor air thermal capacitance.
R_{mi}	– indoor air-thermal mass thermal resistance.
R_{oi}	– indoor air-outdoor air thermal resistance.
$\dot{Q}_{hvac}$	– sensible HVAC heating or cooling (+/- respectively).
$\dot{Q}_{load}$	– internal heat loads due to solar radiation, occupancy, lighting and electrical equipment.

3.2 Assumptions

- In a more sophisticated model, one could model and include the indoor air dynamics, the saturation limits of the HVAC equipment, and the HVAC control dynamics to deliver a T_{ia} controlled to a temperature set point (T_{sp}). However, for the purposes of this work, these dynamics are combined and T_{ia} is modeled to be equal to the room temperature set point (T_{sp}) with a constant derivative limited to ±2 °C/hr. This greatly simplifies the modeled equations and also reduces the number of model parameters to be fit. Considering that most HVAC equipment (with temperature control) will not deliver a response faster than this, this is not a bad assumption and not critical to the results.
- Also, for the purposes of this work, the coefficient of performance (COP) is assumed to be constant with a value of 3.0. It is the ratio of the amount of cooling performed to the energy input to the compressor. Energy delivered to fans is much smaller than the energy delivered to the compressor and is ignored.
- The HVAC equipment has sufficient capacity to maintain and deliver the desired temperature setpoint.
- By combining and modeling the dynamics of the zone air and the HVAC control and saturation as a constant derivative, it is sufficient to use a time step of 0.5 hours to capture the remaining dynamics.
- The simulated HVAC system and the model used within the MPC, employ the same model.
- There is no discrepancy between predicted and actual loads.

3.3 Modeled Equations

The non-steady state difference equations comprising the model are shown:

$$T_{ia,i}(k+1) = T_{sp,i}(k+1) \quad \text{(Note: } (T_{sp,i}(k+1)-T_{sp,i}(k))/\Delta t \text{ will be limited by optimization)} \tag{1}$$

$$T_{m,i}(k+1) = T_{m,i}(k) + \Delta t \cdot (T_{ia,i}(k)-T_{m,i}(k)) / (C_{m,i} \cdot R_{mi,i}) \tag{2}$$

$$\dot{Q}_{m,i}(k+1) = (T_{ia,i}(k+1)-T_{m,i}(k+1)) / R_{mi,i} \tag{3}$$

$$\dot{Q}_{oa,i}(k+1) = (T_{ia,i}(k+1)-T_{oa,i}(k+1)) / R_{oa,i} \tag{4}$$

$$\dot{Q}_{ia,i}(k+1) = C_{ia,i} \cdot (T_{ia,i}(k+1)-T_{ia,i}(k)) / \Delta t \tag{5}$$

$$\dot{Q}_{hvac,i}(k+1) = \dot{Q}_{ia,i}(k+1) + \dot{Q}_{m,i}(k+1) + \dot{Q}_{oa,i}(k+1) - \dot{Q}_{load,i}(k+1) \tag{6}$$

$$\dot{Q}_{clg,i}(k+1) = -\min(0, \dot{Q}_{hvac,i}(k+1)) \tag{7}$$

$$\dot{Q}_{htg,i}(k+1) = +\max(0, \dot{Q}_{hvac,i}(k+1)) \tag{8}$$

$$\dot{Q}_{clg,sum}(k+1) = \sum_i \dot{Q}_{clg,i}(k+1) \tag{9}$$

$$\dot{Q}_{htg,sum}(k+1) = \sum_i \dot{Q}_{htg,i}(k+1) \tag{10}$$

$$W_{hr}(k+1) = \max(\dot{Q}_{clg,sum}(k+1), \dot{Q}_{htg,sum}(k+1))/COP \tag{11}$$

where:

- Δt – time step (= 0.5 hours).
- i – zone index(1,2).
- k – discrete time step index.
- $T_{sp,i}$ – temperature set point of zone i.
- $\dot{Q}_{m,i}$ – enthalpy into building mass of zone i.
- $\dot{Q}_{oa,i}$ – enthalpy lost to outdoor of zone i.
- $\dot{Q}_{ia,i}$ – enthalpy into indoor air of zone i.
- $\dot{Q}_{hvac}$ – enthalpy provided to the zone via the HVAC to zone i.
- $\dot{Q}_{clg,i}$ – cooling provided by the HVAC to zone i (note sign adjust).
- $\dot{Q}_{htg,i}$ – heating provided by the HVAC to zone i.
- $\dot{Q}_{clg,sum}$ – total cooling provided by the HVAC (note sign adjust).
- $\dot{Q}_{htg,sum}$ – total heating provided by the HVAC.
- W_{hr} – total electrical energy required for a heat recovery VRF system.

3.4 Non-Linear Optimization

The concept behind economic MPC is to minimize the cost over the entire horizon. Performing such an optimization (or minimization) for the MPC will require a non-linear optimization due to the presence of the min and max functions and the constraint on the derivative of T_{sp}. This work investigates the impact that MPC can provide to heat recovery VRF units. The economic MPC that minimizes cost over the horizon is formulated as shown:

$$C^*_{horizon} = \sum k \; W_{withhr}(k) * UR(k) \tag{12}$$

Subject to the constraints:

$$T_{sp,i}(k) \geq T_{min,i}(k)$$
$$T_{sp,i}(k) \leq T_{max,i}(k)$$
$$T_{sp,i}(k) \geq T_{sp,i}(k-1) - \Delta_{max} \cdot \Delta t$$
$$T_{sp,i}(k) \leq T_{sp,i}(k-1) + \Delta_{max} \cdot \Delta t$$

where:

- $C_{horizon}$ - Cost of HVAC over the entire horizon.
- $T_{min,i}(k)$ - The minimum allowed zone temperature for zone i at time k.
- $T_{max,i}(k)$ - The maximum allowed zone temperature for zone i at time k.

Δ_{max} - The maximum derivative of zone temperature under HVAC control. (2 °C/hr).
UR(k) - The rate of the electricity ($/kwh) at time k.

*This cost function does not include a demand charge due to the fact that this work relates to residential or light commercial HVAC.

3.3 Simulation

Baseline and MPC simulations were performed on 52 days selected evenly spaced throughout the year. Outdoor temperature and solar values were gathered from a Typical Meteorological Year (TMY) for Milwaukee, WI. Internal and occupancy loads were derived from previous work by Chinde (2016).

Baseline temperature set point was set to 23 °C. The MPC temperature boundaries (T_{min} and T_{max}) were established on both sides of the baseline set point. During occupied conditions this band was ±1 °C. During unoccupied conditions, the set point band was ±4 °C. The occupied period ran from 6am to 7pm daily.

The utility rate was set to the value for Milwaukee utility. The utility rate was 0.10 $/kwh during off peak conditions and rose to 0.30 $/kwh during the peak period of noon to 7pm.

Model parameters for light commercial Milwaukee building zones of 200 m^2 were established from first principles and measured data, Chinde (2016):

- C_m = 4.78 [kwh/C] (lumped mass thermal capacitance)
- C_{ia} = 0.21 [kwh/C] (indoor air thermal capacitance)
- R_{mi} = 0.85 [C/kw] (indoor air-thermal mass thermal resistance)
- R_{oi} = 3.52 [C/kw] (indoor air-outdoor air thermal resistance)

The two zones used for this model, were established with different disturbance profiles in order to be able to utilize the heat recovery mode of the VRF system. In general, zone 1 was set up to require more cooling that zone 2. Zone 2 was established with a plug profile 1/5th of the normal plug and occupancy profiles of zone 1. Zone 1 was also modeled with a southern exposure, while Zone 2 was modeled with a northern exposure.

The Matlab function, fmincon was employed to perform the minimizations. This is a non-linear, bounded, multi-variate optimization algorithm. An example of the simulation is shown below in Figure 3. Each simulation generates a baseline cost where the baseline temperature setpoint is maintained, and an MPC cost where the temperature setpoint is maintained within a band around the baseline temperature.

One zone

As one can see in this figure, the MPC algorithm provides an optimal temperature setpoint for each zone.

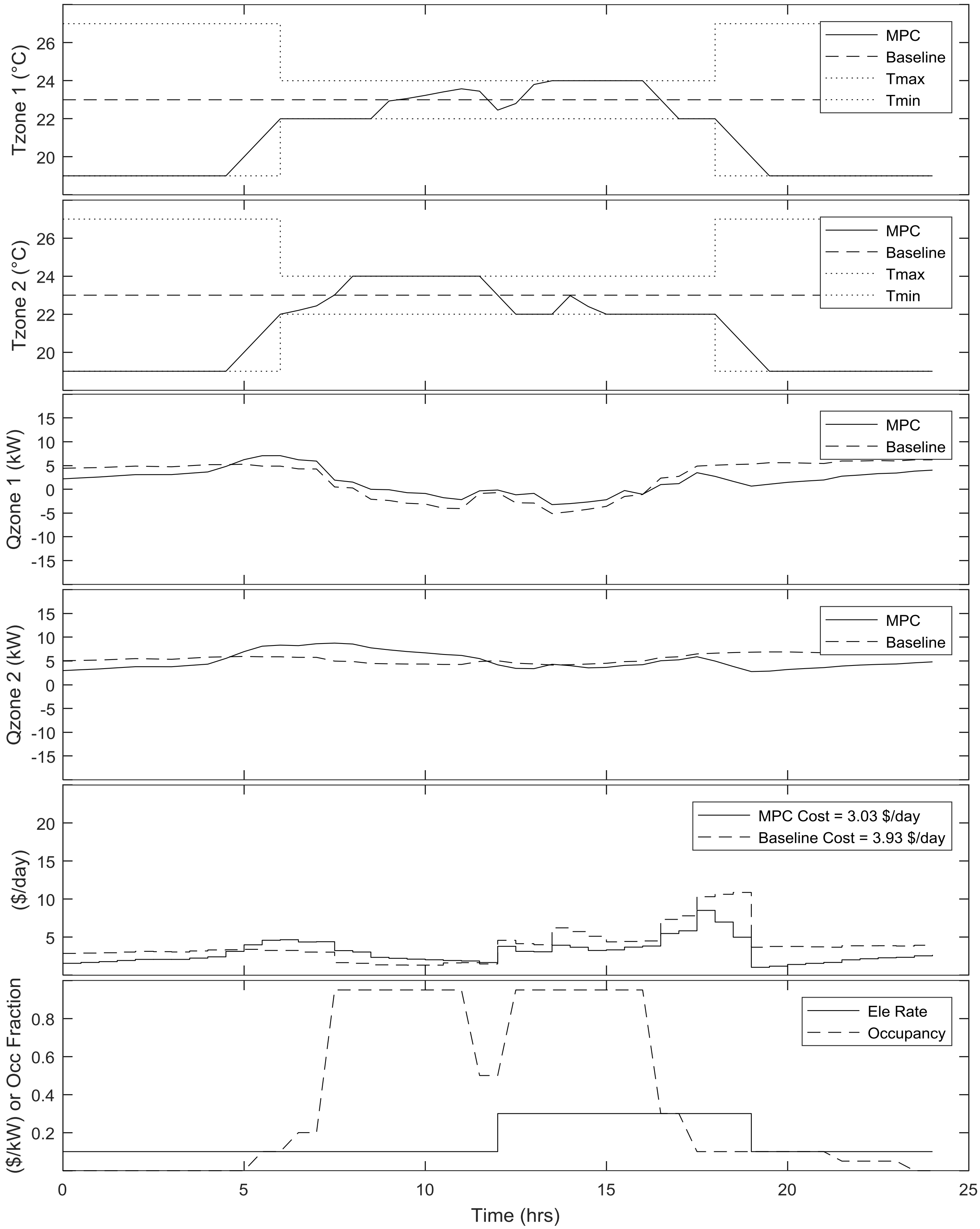

Figure 3: Typical Single Day Simulation

4. RESULTS AND ANALYSIS

Cost and enthalpy data were gathered from each simulation. The following tables summarize the simulation results.

Table 1: HVAC Heat Loads (Daily Averages)

	Heating			Cooling		
Season	**Baseline (kW)**	**MPC (kW)**	**Improvement**	**Baseline (kW)**	**MPC (kW)**	**Improvement**
Winter	5.76	5.01	13.0%	0.41	0.19	54.4%
Spring	2.00	1.29	35.6%	1.56	1.21	22.6%
Summer	0.50	0.12	75.1%	2.59	2.25	13.2%
Fall	3.19	2.53	20.6%	0.95	0.73	23.8%
Year	2.86	2.24	21.8%	1.38	1.09	20.8%

Table 2: HVAC Power Required (Daily Averages)

Season	Baseline (kW)	MPC (kW)	Improvement
Winter	1.49	1.27	14.7%
Spring	0.98	0.67	31.8%
Summer	0.99	0.78	21.4%
Fall	1.06	0.79	25.3%
Year	1.13	0.88	22.4%

Table 3: HVAC Cost

Season	Baseline ($/day)	MPC ($/day)	Improvement
Winter	5.13	4.21	17.8%
Spring	3.88	2.59	33.2%
Summer	4.49	3.41	24.1%
Fall	3.85	2.78	27.8%
Year	4.34	3.25	25.1%

The results show that the MPC algorithm is capable of reducing HVAC energy by efficiently utilizing the allowed temperature band around the desired setpoint. Additional cost savings are also achieved as the algorithm makes use of the building mass to shift HVAC loads from the higher priced times of the day to the lower priced times.

5. CONCLUSIONS

One can see that the potential savings from applying MPC to VRF systems is significant. Savings of energy and cost can be obtained. The results are shown to be good for the VRF systems employing heat recovery. The improvement in cost due to MPC is projected to be 25%. These results will depend on the accuracy of the model and the prediction of the disturbances. It can also be seen that the cost for the heat recovery operation in general is less than the cost for non-heat recovery.

REFERENCES

Chinde, V. (2016). EOS – Relationship Between User Inputs and Kernel Inputs for the Glas MPC Planning Tool. Milwaukee, WI: Johnson Controls Internal White Paper.

Ellis, M. J., Wenzel, M. J., & Turney, R. D. (2016). System Identification for Cascaded Model Predictive Control of Building Region Temperature Applications. In *Proceedings of the 4th International High Performance Buildings Conference* (pages). West Lafayette, IN.

Ellis, M. J., & Wenzel, M. J. (2017). EOS – Building Mass Storage: Model Predictive Control for Buildings. Milwaukee, WI: Johnson Controls Internal White Paper.

Ma, J., Qin, S. J., Salsbury, T., & Xu, P. (2012). Demand reduction in building energy systems based on economic model predictive control. *Chemical Engineering Science, 67*, 92–100.

Mendoza-Serrano, D. I., & Chmielewski, D. J. (2012). HVAC control using infinite-horizon economic MPC. In *Proceedings of the 51st IEEE Conference on Decision and Control* (pp. 6963–6968). Maui, HI.

Patel, N. R., Risbeck, M. J., Rawlings, J. B., Wenzel, M. J., & Turney, R. D. (2016, in press). Distributed economic model predictive control for large-scale building temperature regulation. In *Proceedings of the American Control Conference*. Boston, MA.

Tapiero Bernal, J. E, & Ellis, M. J. (2017). Building Thermal Mass Energy Storage Control-Oriented Model and Parameter Identification. Milwaukee, WI: Johnson Controls Internal White Paper.

Touretzky, C. R., & Baldea, M. (2014). Integrating scheduling and control for economic MPC of buildings with energy storage. *Journal of Process Control, 24,* 1292–1300.

Turney, R. D., & Wenzel, M. J. (2012). Model predictive control (MPC) for demand response (Tech. Rep.). Milwaukee, WI: Johnson Controls Internal White Paper.

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