Case Study: Predictive Control of Refrigerated Facilities for Improved Energy Management

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ABSTRACT

This paper provides an overview of a predictive refrigeration control technology being developed by the CSIRO, including initial results from a real-world case study at Newcastle, NSW Australia. The technology is designed to intelligently alter the operation of a refrigeration system by dynamically determining optimal operating temperature set-points and run-time schedules to reduce energy consumption and operating costs, whilst maintaining local constraints such as product quality and safety. Utilising 'self-learning' model predictive control (MPC) techniques from control theory and computer science domains, the technology makes use of forecasting to move away from a reactionary control philosophy. By taking into account anticipated external conditions, electricity tariffs and adaptively learning the thermal response of the system, optimal control and pre-cooling strategies can be employed for harmonising the fundamentally different high level system goals of minimising operating cost and reducing energy consumption, while ensuring internal temperature conditions are satisfied.

***Keywords**: Cold Storage, Energy Management, Model Predictive Control (MPC), Pre-Cooling, Refrigeration.*

1 INTRODUCTION

With rising energy costs and increasing environmental awareness, there is a growing need to reduce energy consumption in the industrial refrigeration sector in Australia. In the earlier paper Estrada-Florez and Platt, 2007, the CSIRO looked at electricity usage in the Australian cold chain from farm gate to consumption, identifying refrigerated distribution (warehousing) as one of the top three sectors with the highest electricity use. As we seek to improve energy performance of commercial and industrial refrigeration systems, an advanced approach needs to be adopted that can optimise system operation based on varying high level goals– namely minimising energy use, CO_2 emissions, and/or operating cost. Considering the various types of energy sources (e.g. electricity from grid, renewables, or distributed generation) and desired indoor environmental operating conditions, predictive control technology can allow an appropriate balance to be found between what are inevitably competing goals. Finding this optimal balance is one of the key functions of the predictive refrigeration control technology being developed by the CSIRO, and allows commercial and industrial refrigeration systems to be operated in a fundamentally different way to conventional systems. This paper provides an overview of CSIRO's predictive refrigeration control technology developed to date, having successful applied similar techniques to the intelligent control of HVAC systems in commercial buildings (Ward *et al*., 2008).

A survey and benchmarking study in Europe (ICE-E, 2012) showed the potential for energy savings in this sector is around 30-40%, achievable by optimising usage of the stores, and repairing or retrofitting the current equipment. A recent technology report (OEH, 2011) produced by the NSW Government Office of Environment and Heritage (OEH) outlines 15 energy saving technologies and techniques available to increase the energy efficiency of an industrial refrigeration plant, ranging from equipment upgrades through to plant process and control optimisation and maintenance. The technologies with the greatest potential to save energy (based on implementation on previously un-optimised plant) included:

1. Variable plant pressure control (12% savings[1]);
2. Automated compressor staging and capacity control (15% savings[1]);
3. Remote control optimisation of refrigeration plant (8% savings[1]); and
8. Refrigeration plant design review (10% savings[1]).

The predictive control technology presented herein can be considered as an automated supervisory control strategy, i.e. being concerned with the optimal control of the overall plant to achieve higher-level system objectives such as energy

[1] Estimated energy savings potential for un-optimised (inefficient plant) based on examples given in report (OEH, 2011).

and cost savings (taking into account information such as weather forecast and electricity pricing information), as opposed to local-level control such as system components and parameters controlled by PID control loops. Referring back to the technology options listed in the OEH report, CSIRO's predictive control technology could be categorised as a combination of Technology 3 and 6, i.e. Remote control optimisation of refrigeration plant; and Variable cold store temperatures. Moreover, the technology could be extended to also include automated compressor staging; however, this is not considered in this preliminary case study.

An inherent advantage of CSIRO's predictive control technology is that in addition to saving energy, it facilitates demand management control strategies through its ability to adaptively predict operating conditions and energy consumption several hours or even days ahead, based on given control scenarios. This makes it ideally suited to devising optimal control strategies in advance that have maximum impact in terms of operating cost savings and/or energy efficiency. Unlike many other energy saving technology options that require major equipment upgrades or installation of expensive instrumentation and sensors, the technology presented herein is designed to be sensor minimal, in that a basic working implementation requires only ambient and room temperatures, plant power consumption and the ability to dynamically adjust the room temperature set-point.

The remainder of this paper is structured as follows: Section 2 provides an introduction to advanced control techniques for refrigerated facilities related work in the field, and gives an overview of model predictive control and its application to refrigerated systems. Section 3 presents some preliminary results from a real-world case study on a small scale facility in Newcastle NSW Australia, with Section 4 providing conclusions and future work.

2 ADVANVANCED REFRIGERATION CONTROL FOR IMPROVED PERFORMANCE

2.1 Application to Commercial Refrigeration Systems

Due to the thermal capacity of the refrigerated products stored in cold storage, this thermal capacity can be utilised to shift all or part of the cooling load in time, therefore enabling benefits in terms of when the refrigeration plant is run and at what capacity based on operating efficiency and/or operating cost objectives. Of course it is essential to ensure product temperatures and temperature excursions remain within certain constraints. These constrains are chosen in such a way that they have no or little impact on product quality or safety. One such investigation into quality attributes of frozen foods undergoing temperature fluctuations (freeze-thaw cycles) is given in Night Wind, 2008b. As larger cold storage facilities and refrigerated warehouses typically store a high quantity of product and hence exhibit considerable thermal capacity, we can exploit the fact that the dynamics of the temperature in the cold room are rather slow, and are therefore advantageous in enabling load shifting or load shedding events over multiple hour time frames.

In seeking to improve the performance of refrigeration facilities, there are opportunities through both equipment upgrades/reconfiguration and optimised system (control) management. It is the later that we focus on. In systems where the refrigeration plant is not undersized, and some level of temperature fluctuation is allowable in the cooled space, key energy management opportunities are:

1. Energy savings through scheduling compressor operation towards times of cooler ambient temperatures (such as overnight) where the system COP is higher. Using the 'rule of thumb' of 2-4% energy saving though each 1°C reduction in temperature differential (Carbon Trust, 2000), and reference mean yearly weather data for our test site (see Figure 1), this could offer around 15% energy savings for a typical site and 30% for a site with consumption biased towards hotter periods of the day;
2. Energy savings through managing compressor operation to take advantage of higher compressor efficiencies at different loadings (typically avoiding part-loading). Depending on the particular equipment used, part load efficiencies can be half that of peak efficiency (Sustainability Victoria, 2009);
3. Cost savings through scheduling compressor operation towards times of cheaper energy costs (such as overnight); For example, as shown in Figure 2, the Energy Australia Loadsmart business tariff is 50% cheaper in off peak times.
4. Cost savings through scheduling compressor operation outside times of peak site load and responding directly to measured site loads to minimise peak demand charges;
5. Cost and energy savings through scheduling the defrost cycle outside of peak demand times; and
6. Cost savings through scheduling compressor operation in response to 'demand management' signals where either the supplying DNSP or retailer offers such a program.

In order to best take advantage of these opportunities, the refrigeration facilities control system requires access to additional data feeds than would typically be available for such a controller. Specifically, we make use of:

- Real-time weather forecasts from the BOM (Bureau of Meteorology), which are then localised based on correlations with historic local weather measurements;
- Measured whole of site energy consumption to allow management of capacity charges; and
- Energy pricing data – typically fixed TOU tariffs plus capacity charges, though the facility has been included for this to use real-time signalling from either:

  – AEMO – responding to wholesale energy prices;
  – DNSP – responding to distribution network constraints;
  – Retailer – managing the retailers exposure to wholesale energy prices; or
  – an energy services provider – providing an aggregated demand response service.

Using these additional data sources, the compressor run schedule for the refrigeration facility is optimised using MPC.

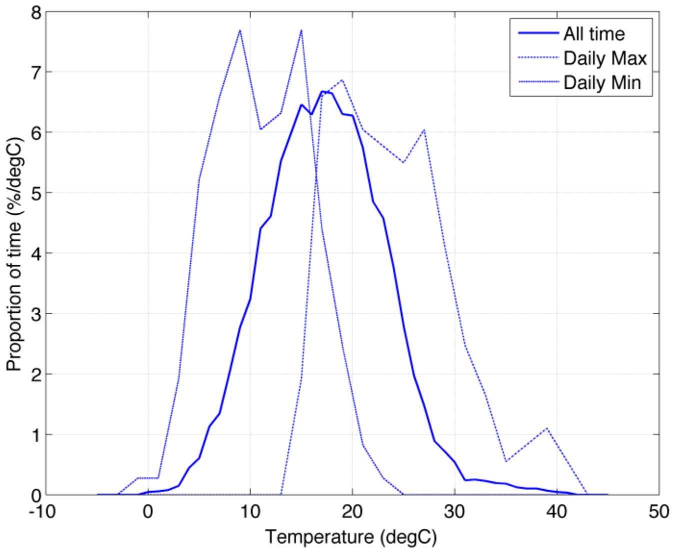

Figure 1. Annual temperature distributions for the test site. Showing distributions of (a) full data; (b) daily maximum temperatures; and (c) daily minimum temperatures. Mean temps. for these distributions are 17.4, 24.0 & 11.2°C respectively.

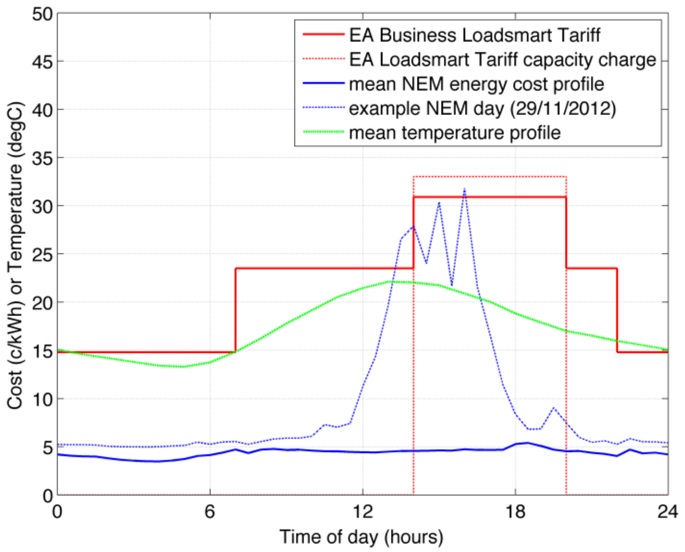

Figure 2. Variations in energy costs throughout the day – data is shown for Energy Australia (EA) LoadSmart Business Tariff, National Energy Market (NEM) wholesale energy prices (for 2012). Mean site dry-bulb temperature is also shown.

2.1.1 Related Work

A number of examples exist in the literature where cold storage facilities and refrigerated warehouses have been used for energy management and control strategies, including load reduction and load shifting (i.e. shifting load to different time), providing ancillary services to the power grid, or for storing excess energy from renewable energy systems (such as wind turbines). Some such examples are listed as follows.

An overview of the potential for load shedding and load shifting from baseline electricity use in response to demand response (DR) events is presented in Lekov *et al*., 2009; Goli *et al*., 2011. This work analysed data from two case studies and nine facilities in California, confirming the DR abilities inherent to refrigerated warehouses but showed significant variation across facilities. In one of the case studies, a 900 kW facility conducted several test DR events in the spring of 2008, in which the refrigeration units serving the freezer were turned off, the temperature set-point of the HVAC system was raised, and battery charger banks were turned off. These strategies enabled the facility to shed about 25% of its total load, with a maximum load reduction of 330 kW.

The work in Hovgaard *et al*., 2011; Hovgaard *et al*., 2012, introduced a novel economic-optimizing MPC scheme for supermarket refrigeration systems that reduces operating costs by utilising the thermal storage, with cost savings between 9% and 32%. The analysis was performed using model based simulation, verified against data logged from real-world systems. Thermal capacity is utilised to shift the load in time, while keeping the temperatures within certain bounds. The economic MPC also has the ability to adjust the power consumption profile to the power supply. The paper specifically addresses advantages coming from daily variations in outdoor temperature and electricity prices but other aspects such as peak load reduction were also considered.

As a final example, the Night Wind project (Night Wind, 2008a) looked at using refrigerated warehouses as giant batteries (i.e. energy storage) for wind energy. The objective was to be able to store all electricity produced by wind turbines all over Europe during night time, and to release this energy again during the peak electricity demand hours in the day time. Implementation involved each cold store refrigeration system requiring installation of a Night Wind Control System (NWCS), where the NWCS was operated by the cold store itself. With the NWCS basing its control decisions on a physical model of each refrigeration system and knowledge of loading, significant data was required to be collected to setup each implementation. This included physical data on the cold store (location, geometries, and construction/insulation materials), refrigeration plant and energy consumption data, and inventory quantities and scheduling. Once the NWCS is setup and programmed for each implementation, it is able to define the optimum capacity for the next 24 hours based on product temperature constraints, electricity prices and wind energy production.

Although the many examples given in the literature show benefits in terms of demand management (i.e. load shedding and load shifting), very few examples exist on optimal supervisory control strategies for saving energy and reducing carbon emissions- of which the technology presented herein aims to address.

2.2 Model Predictive Control of Refrigeration Systems

Model-based predictive control (MPC) refers to a class of feedback control strategies that optimise in real time the behaviour of a system using available current measurements and state predictions obtained using a dynamic mathematical model. Measurements and predictions are used to compute a control signal that determines the system response to current and future conditions within a pre-specified time horizon by solving an optimisation problem that selects the best control sequence against a suitable performance cost function minimising, for example, set-point deviations and/or operating costs (Camacho and Bordons, 1998). The first element of the control sequence is applied to the system, and then the optimal control sequence is subsequently recalculated using new measurements and predictions, repeating the optimisation at every control interval in a receding horizon process.

MPC has rigorous stability and robustness analysis (Mayne *et al*., 2000), and has been applied for more than 3 decades in a wide range of process industries, including oil and gas, food processing, chemicals, and automotive (Camacho and Bordons, 1998; Qin and Badgwell, 2003). MPC has been recently proposed for flexible and efficient power consumption of commercial refrigeration systems (Hovgaard *et al*., 2011; Hovgaard *et al*., 2012).

2.2.1 Mathematical Model of Freezer Temperature Dynamics

A mathematical model of the dynamic response of the system is a key component of MPC. This model may be obtained from physical principles, with parameters obtained from knowledge of the system size and components; as a “black-box” model, by postulating an appropriate model structure with parameters fit using experimental data; or as a “grey-box”, where the model structure may be partially or totally obtained from physical principles, but parameters are fit using experimental data. We follow the latter approach and derive a mathematical model to describe the dynamics of the freezer room temperature as a function of freezer power-demand, ambient temperature, and freezer set-point. We will then fit the parameters of two simple grey-box model structures using linear regression analysis.

In the system considered the freezer-room temperature is controlled by relay control with hysteresis. The dynamics of the freezer temperature $x(t)$ may be approximately described by a first order linear differential equation of the form

(1) $$\mathrm{dx(t)/dt = a(x(t) - x^a(t)) - \; b\, u(t)},$$

where the rate of change in the freezer room temperature $\mathrm{dx(t)/dt}$ is expressed as a function of the ambient temperature outside the room $\mathrm{x^a(t)}$, and the cooling action of the compressor as a control signal $\mathrm{u(t)}$. The positive constants $\mathrm{a, b}$ group physical parameters such as room thermal resistance and capacitance.

The control signal $\mathrm{u(t)}$ typically regulates the room temperature using a switching rule with hysteresis in the form

(2) $$u(t) \; = \begin{cases} U_{on}\text{, cooling} - \text{on mode, when } x(t) \geq x^{SP} \\ U_{off}\text{, cooling} - \text{off mode, when } x(t) \leq x^{SP} - \Delta \\ u(t)\text{, otherwise} \end{cases}$$

where x^{SP} represents the freezer-room temperature set-point, and Δ the regulation temperature differential. Typically data is collected by sampling, so a more useful version of (1) is the discrete-time difference equation

(3) $$x_{k+1} = \alpha\left(x_k - x_k^a\right) + x_k^a - \beta u_k, \qquad k = 0,1,2,\ldots$$

where $x_k = x(kh)$, $x_k^a = x^a(kh)$ and $u_k = u(kh)$, and the parameters $\alpha = e^{-ah}$, and $\beta = be^{-ah}/a$. From the physical relations in (3), we write the standard *autoregressive* model structure with external inputs (ARX model structure)

(4) $$x_{k+1} = \theta_1 x_k + \theta_2 x_k^a - \theta_3\, u_k,$$

where $u_k = P$ in cooling-on mode, and $u_k = 0$ otherwise. Equation (4) may be viewed as a way to *compute* the next value of the room temperature output x at time $k+1$ given previous observations of room temperature, ambient temperature and control input at time k, and the system parameters. We turn Equation (4) into a practical model to compute a one-step ahead prediction of x, denoted $\hat{x}(k|\theta)$, given observations up to time k as

(5) $$\hat{x}(k|\theta) = \varphi^T(k)\theta + e(k),$$

where we have included in the new variable $e(k)$ the effect of measurement noise and sensor offsets. The vector $\varphi(k) = [\, x_k, x_k^a, u_k]$ groups all prior observations, and is usually known as a *regressor*. The model parameters are grouped in the vector $\theta^T = [\theta_1, \theta_2, \theta_3]$.

There exist well-developed system identification techniques to use experimental data to optimally fit parameters to different model structures, including the ARX model in Equation (5) (Ljung, 1999). For illustration, we present in this paper prediction results for two simple discrete-time linear model structures fitted using Matlab System Identification Toolbox™ (Ljung, 2013):

(a) A discrete-time first-order ARX model

$$x_{k+1} = \theta_1 x_k + \theta_2 x_k^a + \theta_3 u_k + \theta_4\, x_k^{SP}$$

where x^{SP} is a time series of the scheduled set-point changes.

(b) A discrete-time second-order state-space model

$$\begin{bmatrix} x_1(k+1) \\ x_2(k+1) \end{bmatrix} = \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix} \begin{bmatrix} x_1(k) \\ x_2(k) \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} \\ \beta_{21} & \beta_{22} & \beta_{23} \end{bmatrix} \begin{bmatrix} x_k^a \\ u_k \\ x_k^{SP} \end{bmatrix}$$

$$x(k) = \begin{bmatrix} \gamma_1 & \gamma_2 \end{bmatrix} \begin{bmatrix} x_1(k) \\ x_2(k) \end{bmatrix}.$$

More elaborated model structures are possible, including nonlinearities and disturbance error models, depending on the accuracy required in the predictions. As we will see in Section 3.2.1, these two simple linear model structures achieve accurate dynamic response predictions, and their parameters may be easily updated to accommodate seasonal variations or freezer loading changes.

2.2.2 Optimisation for Energy/Cost Performance

Having identified a simple model for the operation of the refrigeration facility, the model predictive controller searches through the set of feasible compressor schedules, ensuring that thermal conditions are maintained within acceptable bounds, while minimising energy consumption and operating costs. It is important to realise that minimising energy and operating costs are distinct objectives (and can often be competing), so an optimisation objective function is defined to balance these goals based on the preferences of the facilities manager.

Figure 3 provides a high level schematic of the various measurements and data feeds for the optimal predictive control structure. Weather measurements and forecasts allow compressors to be scheduled to run at their most efficient; energy tariff and demand response options allow schedules to reduce operational costs (possibly at the expense of greater energy use); and whole of site power measurements allow capacity charges to be managed. The balance between saving energy (and hence greenhouse gas emissions) and reducing energy (dollar) costs must be determined according to the goals of the particular client.

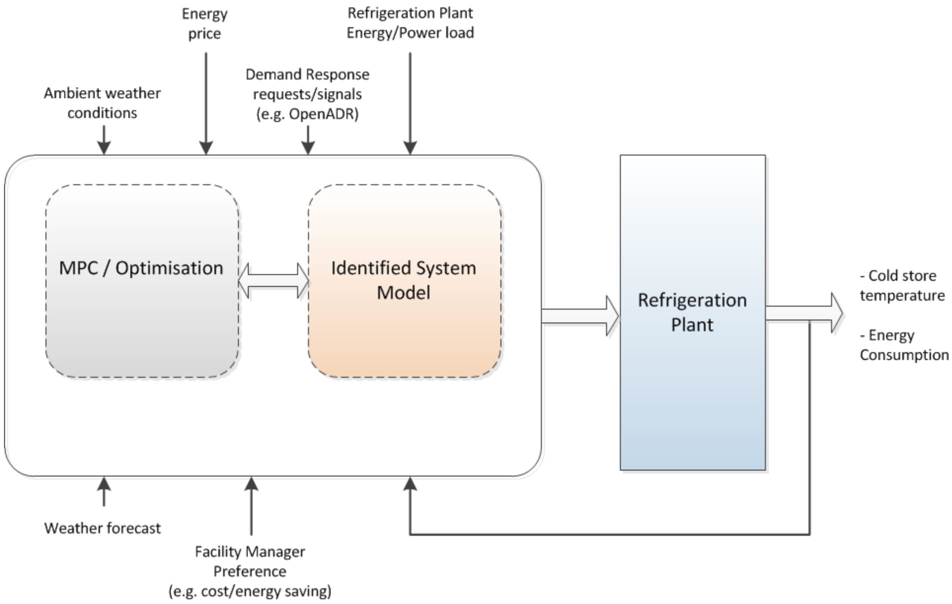

Figure 3. High level schematic of the predictive control technology.

3 REAL-WORLD CASE STUDY

3.1 Cold Storage Facility Overview and Experimental Setup

The facility used in this preliminary case study is located at the CSIRO Energy Centre in Newcastle NSW Australia, consisting of a walk-in freezer room with a volume of approx. 89 cubic metres and dimensions 6.5m (L) x 2.85m (W) x 4.8m (H). The facility was designed to operate at between -18 to -20°C, however the current contents being refrigerated can easily tolerate a more energy efficiency set-point, and hence it currently controlled at around -10°C.

The facility is refrigerated by a Kirby semi hermetic reciprocating air-cooled compressor/condenser unit (model D3DA50X170) operating on refrigerant R404a. The evaporator unit (model KHDF 109) is an electric defrost low temperature coil. Room temperature control is via a Phasefale JouleTemp digital thermostat controller that operates a solenoid valve fitted in the liquid line. Consequently, the condensing unit is a pump down system.

For real-time data collection, Modbus enabled temperature and relative humidity sensors have been instrumented inside the cold storage room and externally (near the compressor/condenser unit) to capture ambient conditions at 1 min. intervals. A Modbus enabled power meter is used to log electrical power and energy data, also at 1 min. intervals. The

JouleTemp digital thermostat controller is Modbus and web enabled, allowing system operational parameters to be dynamically changed when required (e.g. room temperature set-point).

3.2 Experimental Results

3.2.1 Model identification and validation results

The parameters of the ARX and state-space model structures introduced in Section 2.2.1 were fitted by linear regression to data collected at the CSIRO Energy Centre, including ambient temperature, and freezer room temperature and power demand. The freezer temperature and ambient temperature measurements for the data used for identification (8 days: 11520 samples at one sample per minute) are plotted in Figure 4. The first half of the data was used for parameter fitting, while the second half was used for model validation by comparing the model responses (freezer temperature simulated using power and ambient temperature measurements) to actual measurements of freezer temperature. The data segment selected includes several set-point changes.

The parameters fitted are as follows:

(a) For the discrete-time first-order ARX model,

$$x_{k+1} = 0.8856\, x_k + 0.0851\, x_k^a + 0.0008055\, u_k + 1.009\, x^{SP}.$$

(b) For the discrete-time second-order state space model,

$$\begin{bmatrix} x_1(k+1) \\ x_2(k+1) \end{bmatrix} = \begin{bmatrix} 0.8767 & -0.1384 \\ -0.02809 & 0.961 \end{bmatrix} \begin{bmatrix} x_1(k) \\ x_2(k) \end{bmatrix} + \begin{bmatrix} -2.014 \times 10^{-3} & 8.312 \times 10^{-5} & 4.439 \times 10^{-4} \\ -3.583 \times 10^{-4} & 1.653 \times 10^{-5} & -2.064 \times 10^{-5} \end{bmatrix} \begin{bmatrix} x_k^a \\ u_k \\ x_k^{SP} \end{bmatrix}$$

$$x(k) = \begin{bmatrix} 46.77 & -1.787 \end{bmatrix} \begin{bmatrix} x_1(k) \\ x_2(k) \end{bmatrix}.$$

Figure 5 shows identified model validation results, where it can be visually appreciated how the predicted response by the two models effectively matches actual room temperatures, including (after a small transient) tracking of set-point changes. Notice that the validation results are shown with means removed. The observed quality of these models fit is confirmed quantitatively on Table 1, which compares Akaike's Final Prediction Error (FPE) and the Mean-squared Error (MSE)- see (Ljung, 1999), obtained for the two models. The state-space model yields a slightly better fit at the expense of a more complex model structure (12 parameters versus 4 for the ARX model).

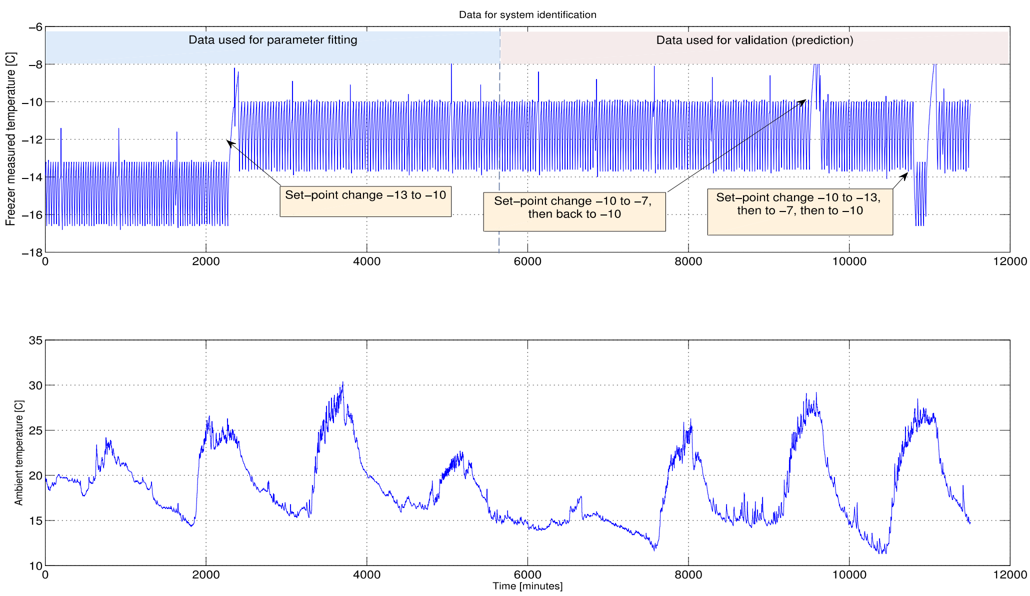

Figure 4. Data used for system identification (11500 samples, at one sample per minute). The first half of the data is used for model fitting, while the second half is used for validation.

Table 1. Goodness of fit.

Model structure	**Final prediction error (FPE)**	**Mean-square error (MSE)**	**Fit to estimation data %**
ARX	0.02415	0.02412	91.82
State-space	0.02139	0.02126	92.32

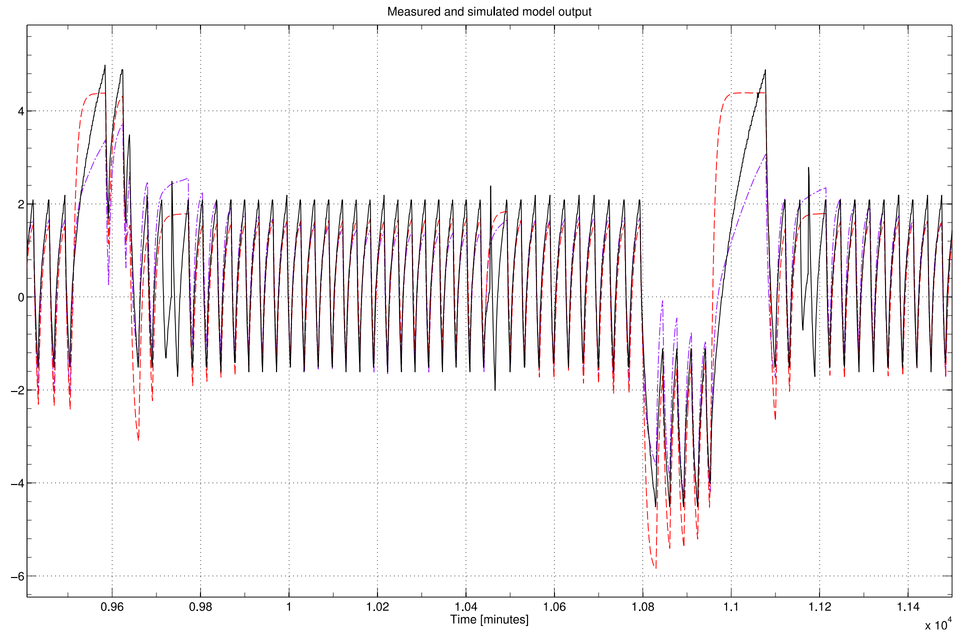

Figure 5. Model validation results for fitted model structures (a) and (b) (see Section2.2.1). Data on the vertical axis is shown with mean value (-12°C) removed.

3.2.2 Set-point change scenarios for power demand shifting

Figure 6 shows a scatter plot of energy per cooling-on cycle versus outside temperature for different freezer temperature set-points, namely -7°C, -10°C and -13°C respectively, captured over summer and autumn months in 2013. As the normal operating set-point for this facility is -10°C, arbitrary set-points both above and below this value (i.e. ±3°C) have been chosen to reflect plausible variations experienced under typical energy management scenarios and to highlight the energy performance of such variance. Based on this data, Table 2 lists indicative energy consumption for ambient temperatures of 20°C and 30°C respectively. The results show that for this particular facility over the time range that data was collected, raising the temperature set-point (i.e. set-point reset strategy) by 3°C results in energy savings of 24% and 30% for ambient temperatures of 20°C and 30°C respectively. Similarly for pre-cooling type energy management scenarios where temperature set-point may be temporarily lowered to store energy in the thermal capacity of the stored product, lowering the temperature set-point by 3°C resulted in increased energy consumption by 7.7% and 16% for ambient temperatures of 20°C and 30°C respectively. Although this type of indoor temperature set-point variation could be performed manually by a facility manager based on detailed knowledge and experience of the refrigeration plant over time, an automated approach could facilitate the selection of optimal set-points for achieving the greatest impact given particular operating objects (e.g. cost or energy savings- or any combination in between), and allow a facility manager to look at 'what if' scenarios before actually changing any actual system set-points or parameters.

Table 2. Indicative energy savings for different room temperature set-points.

	Energy Consumption (%)		
Ambient Temperature	**Reference Set-point (-10°C)**	**Set-point (-7°C)**	**Set-point (-13°C)**
@ 20°C	0% (reference)	-24.27 %	+7.7 %
@ 30°C	0% (reference)	-30%	+16 %

Figure 7 and Figure 8 present the results of two experiments with set-point changes to illustrate the potential for cost savings through power demand shaping. Figure 7 shows the first experiment (set-point reset strategy), where the freezer room temperature set-point is changed from -10°C to -7°C for two hours. We can observe that the power demand is reduced during this period; however some power is still required to maintain the room temperature at the new set-point. In Figure 8 the same set-point change is preceded by a pre-cooling period, where the set-point is first lowered to -13°C. It is observed in this case that no power is consumed during the period at -7°C. This illustrates the potential for cost savings by avoiding peak price electricity periods. Note, however that this particular pre-cooling scenario ends up using *more* energy in total (22.26 kWh) than that the set-point reset strategy (19.08 kWh), which is generally expected. If however the refrigerated facility had much slower dynamics as exhibited in large cold stores and refrigerated warehouses, predictive control technology could perceivably optimise the compressor runtime to occur during more energy efficiency ambient conditions, thus could potentially save some energy in certain circumstances.

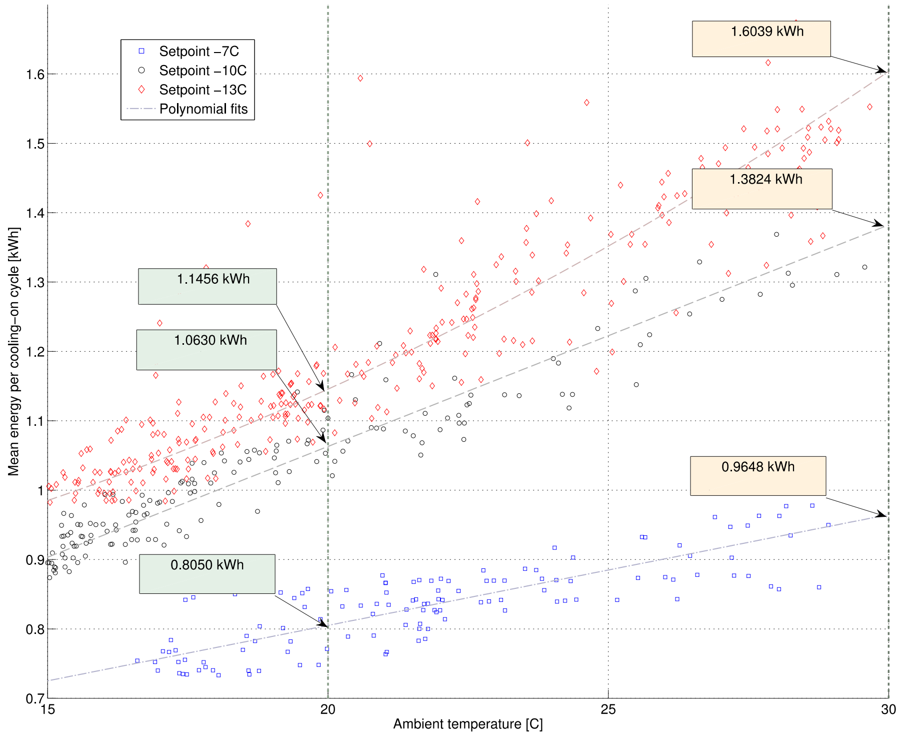

Figure 6. Scatter plot of energy per cooling-on cycle versus outside temperature for different freezer temperature set-points. Text boxes show estimated energy demand over polynomial curve fits to the scattered data for each set-point at 20°C and at 30°C ambient temperatures.

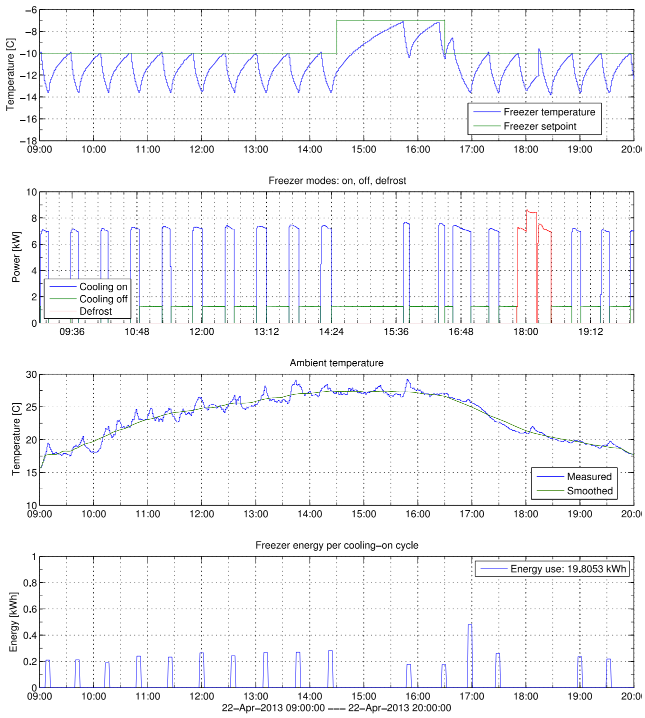

Figure 7. Freezer set-point-reset scenario. Set-point is changed from -10°C to -7°C at 14:30, and is reset to -10°C at 16:30. A defrost cycle may be seen at 18:00.

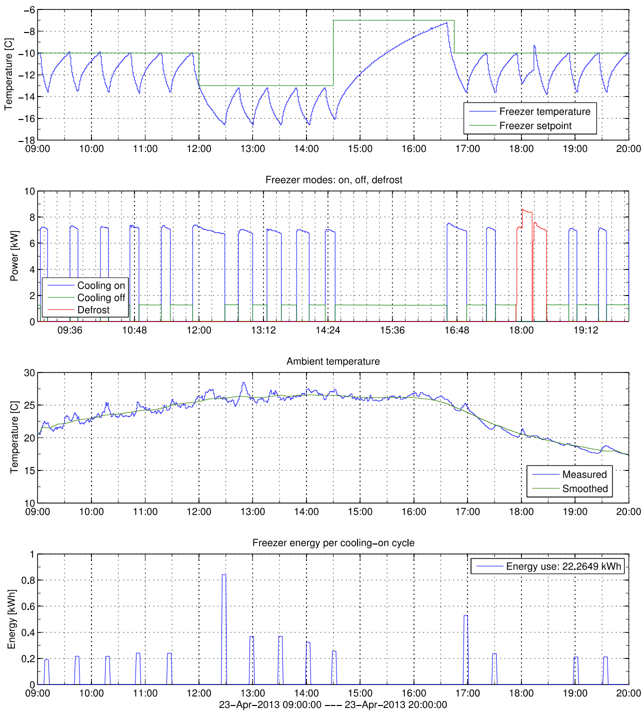

Figure 8. Freezer set-point-reset with pre-cooling scenario. Set-point is changed from -10°C to -13°C at 12:00 (pre-cooling period), changed to -7°C at 14:30, and reset to -10°C at ~ 16:30. It may be seen that no power is consumed during the set-point-reset to -7°C following pre-cooling.

4 CONCLUSION AND FUTURE WORK

This paper has presented preliminary results of a predictive refrigeration control technology being developed and trialled on a small scale facility at Newcastle, NSW Australia, intended to build the case for more advanced control of commercial and industrial refrigerated facilities for achieving both improved operating cost and energy performance. The technology is designed to dynamically determine optimal operating temperature set-points and run-time schedules to reduce energy consumption and operating costs, whilst maintaining local constraints such as product quality and safety. Utilising a 'self-learning' MPC control technique and optimisation framework, the technology takes into account anticipated external conditions, electricity tariffs, and plant power demand to adaptively learn the thermal response of the system, enabling optimal control and pre-cooling strategies to be devised and employed with limited human intervention and without detailed knowledge and understanding of the dynamic plant and facility under control.

Having successfully developed a predictive modelling technique using MPC that is showing accurate prediction of indoor temperature and energy consumption a number of hours into the future, the CSIRO is currently developing the optimisation framework around this to be to able demonstrate a complete system technology for optimising operating cost and energy performance, having previously demonstrated similar technology in the commercial heating, ventilation and air conditioning (HVAC) space achieving savings of up to 45% (Zavala *et al*. 2011). Towards this, the CSIRO is seeking industry trial partners to help in determining proof-of-concept with the benefit of gaining early access to the technology. Thus, the CSIRO Energy Flagship would like to extend an invitation to cold store/refrigerated warehouse owners and operators interested in a collaborative project to explore this opportunity. Please contact the corresponding author by email if interested.

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