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# Micro-grid energy dispatch optimization and predictive control algorithms; A UC Irvine case study

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ABSTRACT

Distributed power and energy resources are now being used to meet the combined electric power, heating, and cooling demands of many buildings. The addition of on-site renewables and their accompanying intermittency and non-coincidence requires even greater dynamic performance from the distributed power and energy system. Load following generators, energy storage devices, and predictive energy management are increasingly important to achieve the simultaneous goals of increased efficiency, reduced emissions, and sustainable economics. This paper presents two optimization strategies for the dispatch of a multi-chiller cooling plant with cold-water thermal storage. The optimizations aim to reduce both costs and emissions while considering real operational constraints of a plant. The UC Irvine campus micro-grid operation between January 2009 and December 2013 serves as a case study for how improved utilization of energy storage can buffer demand transients, reduce costs and improve plant efficiency. A predictive control strategy which forecasts campus demands from weather predictions, optimizes the plant dispatch, and applies feedback control to modify the plant dispatch in real-time is compared to best-practices manual operation. The dispatch optimization and predictive control algorithms are shown to reduce annual utility bill costs by 12.0%, net energy costs by 3.61%, and improve energy efficiency by 1.56%.



## Introduction

Increasing concerns regarding electricity costs, energy reliability, and emissions are encouraging businesses and campuses to consider self-generation and district heating/cooling. Deployment of a combination of electric generators, energy storage devices, district heating/cooling, and electrical circuit infrastructure to meet the energy demands of several buildings comprises a micro-grid [1]. Micro-grids are typically connected to a regional electric utility network that provides supplemental electricity through a single high voltage interconnection. Regional utilities rely upon the temporal smoothing effect of aggregating thousands of dynamic consumer demands. At the micro-grid scale, i.e. 250 kW–50 MW, energy management similarly relies to some extent upon aggregation to temporally smooth demand, but primarily micro-grids must remain highly responsive to demand variations arising from building energy demands and energy supply dynamics caused by on-site renewable generators. High efficiency and low cost operation requires a continuous optimization and dispatch of resources and effective management of energy storage devices to balance power under all circumstances of dynamic load, dynamic generation, renewable intermittency or other perturbations [2]. Thermal energy storage (TES) technology, i.e. cold-water storage, ice, or molten salts, can assist to decouple demand from production. Use of any storage technologies introduces a time horizon to the dispatch optimization, which can be further complicated by physical and operational constraints.

This study will evaluate the impact of cold-water storage on the dispatch and control of a suite of non-uniform chillers, and the ability to time-shift electric demand from on-peak rate periods. Energy storage can substitute for additional ‘peaker’ generation for avoiding peak demand charges caused by building dynamics or intermittent renewable generation. High levels of renewable power generation installed within environmentally motivated communities will increasingly require smart grid technologies to balance generation and reduce the burden placed on the regional utility [3]. This study uses the campus of the University of California, Irvine, as a micro-grid, one which already has 1 MW of solar power installed and that is scheduled to quadruple its solar installations to more than 4 MW in the next several years.

The cost and emission benefits of district heating/cooling stem from utilization of larger and more efficient boilers/chillers,

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**Nomenclature**

| | |
|---|---|
| COP | coefficient of performance |
| GT | gas turbine |
| kW | kilowatt |
| MW | megawatt |
| SCE | Southern California Edison |
| ST | steam turbine |
| TES | thermal energy storage |
| UCI | University of California, Irvine |

aggregation of multiple building loads to reduce the necessary capacity and level load fluctuations, reduced maintenance of fewer individual systems, and improve reliability through redundancy of the co-located systems. Centralized infrastructure and time-of-use energy costs have made thermal energy storage a cost-effective solution for micro-grid applications. Large thermal reservoirs introduce the capability to manage cooling dynamics for lower emissions and energy costs [4]. District heating/cooling applications can save money by utilizing energy storage to shift on-peak production to cheaper off-peak hours. In some climates electric cooling loads comprise more than 50% of building mid-day energy demand, enabling substantial reductions of on-peak demand charges through demand shifting. Reduced on-peak energy use and demand charges from cold-water storage in combination with improved chiller efficiency due to cooler nighttime temperatures provide for substantial savings in warm climate applications.

The University of California, Irvine campus has the capacity to self-generate 90% of its annual electricity demand, and employs district heating/cooling with cold-water storage. The campus balances its self-generation through interconnection with the local utility, though it is capable of operating as an independent grid throughout most of the year, and will soon have sufficient distributed generation capacity to provide black-start capability for the primary co-generation plant. The campus interconnection with the grid is changing from a minimum import threshold to an inadvertent export agreement allowing the University to self-generate nearly 100% of its demand while it has the capacity to do so. The campus plant, outlined in Fig. 1, includes seven co-located chillers, of varying size and performance characteristics, a 13.5 MW gas turbine, a 4.5 MW steam turbine generator, and a 175 MW h cold-water storage tank.

The cold-water storage meets the daily cooling demand during on-peak electric rate hours through the fall, winter and spring seasons, but must be supplemented with daily chiller operation during hotter summer days. Electricity production is supplemented by more than 1 MW (peak) of stationary rooftop and concentrated dual-axis tracking solar photovoltaic power generators, and through interconnection with the regional electric utility, Southern California Edison (SCE). This complex and integrated micro-grid serves as the case-study for this analysis, though the optimization techniques developed and demonstrated apply to any cooling plant with multiple chilling units and cold-water storage. The constraints faced by the UC Irvine plant are similar to those of any chiller plant; the chillers must operate near rated capacity for optimal efficiency, excessive start-ups and shut-downs must be avoided, and energy costs, including demand charges, are considerably higher during peak demand hours.

The interconnection agreement between UC Irvine and SCE during the time of this study (2010–2013) sets a time-of-use rate schedule for energy use and demand charges and also stipulates that >1 MWe must be continuously imported by the campus. This minimum import constraint is common among micro-grids and largely dictates the operating procedures associated with all of the cooling, heating and power equipment. Electric demand fluctuations on the order of 150 kW are seen in the high resolution campus demand data, thus a considerable safety margin of 30% was applied to the minimum purchase threshold. Both energy use charges, the electricity drawn (kW h), and demand charges, the peak load (kW), are measured and billed on a monthly cycle. Daytime (on-peak) electricity is charged at a higher rate than night-time (off-peak) electricity use, and summer rates are substantially higher for both energy use and peak demand charges. Nearly half of the utility cost is associated with a departing load charge of 1.3 ¢/kW h of campus generation.

Currently, the plant staffs three 8-h shifts of two operators to manage the dispatch and operation of the GT, chiller plant, cold-water thermal energy storage (TES) and district heating/cooling loops. General guidelines regarding start-up sequence of the chillers and the operators' personal intuition and experience determine the real-time dispatch of the electric chillers, the daily charge capacity and charge/discharge schedule of the TES, and the set-point for both electric generators. Analysis of historical data demonstrated the substantial financial savings that accrue to UC Irvine by shifting electric demand with the cold-water storage, but such analyses also indicated that the cold-water storage was underutilized. Optimization of the plant dispatch dynamics through linearization and heuristics for plant operation could present an opportunity for cost and emissions savings. This work develops and applies techniques to improve the dispatch of the entire plant using day-ahead weather forecasts, simplified dynamic models, and historical use patterns. Real-time feedback of demand and storage capacity is used in the development of a predictive control strategy that automates the plant dispatch. Real-world testing is underway using a man-in-the-middle approach, wherein the plant operators have the optimized dispatch information available at their disposal.

Dynamic dispatch of distributed resources is currently an intensely studied problem due to the rapid increase of renewable generator deployment in some regions [5]. Means of energy storage such as batteries [6], thermal storage [6], pumped hydro, or hydrogen storage [7] have been proposed as partial solutions for managing intermittency. Common strategies consider renewable power as a negative load and dispatch alternatives accordingly to complement the non-dispatchable renewable sources and loads [8]. Management of distributed resources near the renewable power source is seen as the most effective means of increasing renewable penetration (i.e., the market penetration of renewable power systems) [9]. Many approaches have been suggested including guiding heuristics [10–12], multi-objective approaches like mixed-integer programing [13–15], fuzzy logic [16–18], and particle swarm optimization [16,19,20], as well as hybrid system theory [21] and model predictive control [22]. The economics [11,16–18] and emissions [5,15] of distributed resources have been of particular interest. Clean dispatchable generators such as fuel cells, micro-gas turbines, and hybrid fuel cell gas turbine systems are capable of load following or responding to renewable intermittency [23–25]. These generators in tandem with modern resource management and energy storage can convert a micro-grid into an efficient and stable participant in the utility network.

Considering the well-recognized importance of energy storage as a solution to renewable power intermittency, surprisingly few authors investigate using energy storage as more than a buffer

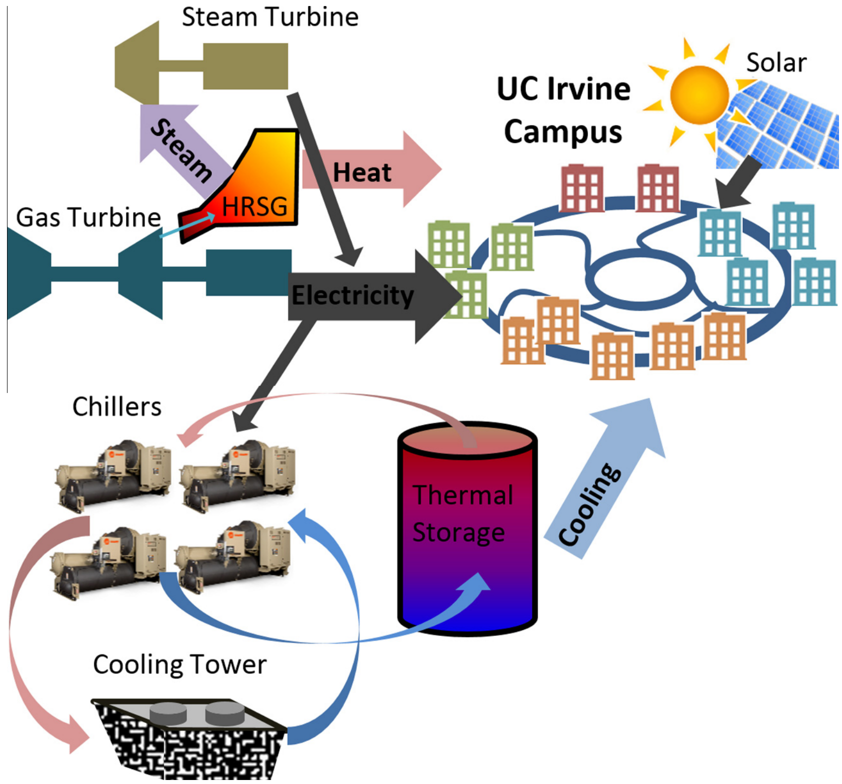


**Fig. 1.** University of California, Irvine Micro-grid.

against the intermittent power source [7]. The majority of optimization schemes focus solely on matching instantaneous demand with optimal efficiency [10,11,15,16,18,19,21]. The large capacity of thermal energy storage systems introduces the additional ability to shift energy demand from peak to non-peak demand hours. This forms a more complex problem requiring system optimization with future forecasting and potentially novel methods of solution.

Here, we present a predictive control approach, which allows for system level optimization over a time horizon and the capability for on-line operation as a micro-grid dispatch strategy. This technique is expected to increase the effective capacity of any storage technologies in a micro-grid, increase the manageable renewable energy penetration and decrease reliance on the external utility grid network. The next section will introduce the UC Irvine micro-grid used in this case study. Section 'Predictive dispatch with feedback' introduces and presents results for a heuristic dispatching methodology with predictive load forecasting. Section 'Chiller dispatch optimization through linearization' presents an alternate dispatching method based upon linear optimization. These approaches can also be applied to the design of future micro-grid networks that are either energy neutral, completely self-reliant or islanded with a combination of renewable power sources, dispatchable generators and energy storage technologies.

## Campus demand & plant description

The University of California, Irvine built a combined cooling heating and power (CCHP) plant capable of meeting the electrical, heating, and cooling demands of the main campus office buildings, laboratory facilities, classroom buildings, and student residences. The features of the Irvine campus are characteristic of a wide variety of universities, corporate campuses, military installations, or other buildings with integrated infrastructure that comprises a micro-grid. This representative campus micro-grid is analyzed and several control strategies are applied in an effort to improve efficiency, emissions and costs.

### *Gas turbine and steam turbine*

A Solar Titan130 gas turbine provides the bulk of the campus electrical power. The turbine operates between 9 and 14 MW depending upon the demands of the campus and the chiller plant. The operating range is constrained to between 9 and 14 MWe by emissions limitations and the ability of the inlet guide vane controls to reduce mass flow in order to maintain high firing temperatures and reasonable efficiency. Despite the inlet guide vanes there is a substantial reduction in thermal efficiency from 33% at nominal power to 26% at minimum power. An inlet air cooling system eliminates dependence upon ambient temperature, but increases the effective campus cooling load on hot days. The efficiency, mass flow rate, and exhaust temperature are utilized to calculate the heat available for capture and conversion to steam in the heat recovery steam generator. The high pressure steam drives the steam turbine and supplies the campus hot water. During emergencies the turbine can respond to transients as fast as 1 MW/min, though standard operation limits manipulation to a rate of approximately 4 MW per hour. Dynamic modeling of the system indicated quasi-steady operation under these slower 15-min transient conditions, and thus a simplified steady-state de-rate curve was used for the efficiency and emission calculations in the current work.

### *Electric chillers/cooling towers*

The electric chillers produce cold water that is circulated throughout the campus. Seven centrifugal electric chillers of varying vintage, capacity, and efficiency and a single stream driven

**Table 1**
UCI chiller plant rated sizes and efficiencies.

| Chiller | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| Size (Tons) | 900 | 900 | 1000 | 2600 | 2800 | 2800 | 3250 | 3250 |
| Size (kWe) | 600 | 651 | 606 | – | 2525 | 2140 | 1905 | 1905 |
| COP | 5.27 | 4.86 | 5.8 | 1.55 | 3.9 | 4.6 | 6.0 | 6.0 |

centrifugal chiller comprise the UCI cooling plant. The coefficient of performance (COP) at rated power, shown in Table 1, ranges from 3.5 to 6. The older units, 1–3, use older refrigerants which are being phased out, and will thus only operate when necessary, while chillers 5–8 use the approved refrigerant R123. Chiller 4 is a steam driven chiller that operates primarily in the summer when sufficient extra steam is available from the co-gen system. During the period in which the data was acquired for plant operation (2011–2013) the steam chiller was out of service, so that comparisons of the predictive control scheme to manual plant operation forced no use of the steam chiller. There is evidence in the most recent data collected supporting additional energy savings from using the steam chiller during summer months.

The effective chiller plant COP is a combination of the individual chillers in operation, and the parasitic draw of the cooling tower fans and pumps. The parasitic load of the cooling towers depends upon the chilled water production, ambient temperature, the number of towers in operation and the condenser water return temperature. Currently there is no control strategy in place to ensure the condenser water return temperature is maintained at the design set-point of 28 °C. This is an area for future improvement and optimization of the chilled water portion of the plant. The cooling tower load is only measured at a pair of transformers, and thus only a simple correlation with chilled water production could be justified from the available campus plant data. The measured cooling tower parasitic was 0.075 kW per ton of refrigeration. As an example this parasitic load reduces the effective COP of chillers 7 & 8 from 6.0 to 5.32.

During electric chiller start-up the inrush current can be as much as 4000 Amps, corresponding to ~2 MW. Under an inadvertent export agreement this start-up current can be met by the grid, but with a minimum import constraint a 2 MW buffer must be initiated before chillers can be restarted. During a chiller re-start the condenser and evaporator take 5–10 min to reach operational temperature. During this transient chilled water production is substantially reduced. The in-rush current and thermal transients are significant enough to discourage starting multiple chillers simultaneously or starting chillers during peak hours. Forethought must be given to how much chilling capacity is necessary to meet chilling demands for the duration of the peak electric rate period. If the chiller starts are always constrained to off-peak hours this transient behavior has a negligible impact on total operating costs or emissions, and can be neglected. Operator experience with maintenance and reliability of the chillers and the combined efficiency of the chillers and cooling towers has led to operating heuristics that constrain individual chiller operation at or near full load capacity while attempting to minimize chiller start/stop events. These insights into plant operation are integrated into both optimization approaches developed herein as constraints in the frequency and time-of-day of chiller re-starts and a constraint to dispatch the chillers only at full load. Therefore the chiller plant can be simplified to a sequence of fixed size units with fixed coefficients of performance as detailed in Table 1.

Three cooling towers are independently dispatched with continuously variable fan speeds for high efficiency. A unique cold-water recirculation loop ensures chiller inlet temperatures do not exceed 11 °C despite the campus return flow ranging from 11 to 18 °C. Rated chiller capacity and efficiency is achieved with a 6.67 °C (12°F) temperature differential. Cold water recirculation ensures a continuous 6.67 °C (12°F) temperature differential for highest chiller efficiency and an output of 4 °C for cooling the campus or charging the TES tank.

*Cold-water storage tank*

The 175 MW h thermal energy storage (TES) tank is used to shift cooling demand from daytime to nighttime. The TES reduces peak daytime demand and increases the base load demand during nighttime hours. The TES stores hot water on top of cold water with a steep thermocline between them. Limited mixing occurs, partially accounting for round trip energy storage efficiency calculated to be 94.7% from the 4 years of data analyzed. This energy storage inefficiency is accounted for as a reduction of the thermal energy sent to the tank during charging. This approach provided the closest correlation with measured data. The cold-water portion of the tank is maintained at 4 °C by the chiller plant. The hot portion of the tank varies according to the campus return temperature that fills it, typically in the range of 12–18 °C. A set of mass flow and energy balance equations that account for losses to the environment are used to determine the charge of the cold-water tank [26]. The height of the thermocline (0–33 m) and the temperature of the hot and cold regions are measured and supplied for feedback calculations.

The design uses the cold-water TES to de-couple the campus water flow rate from the chiller plant flow rate, such that the operating chillers remain at or near full capacity while running and so that chiller operating times need not correspond to times of campus cooling demand. The combined chiller/cooling tower/cold-water storage plant has three operating modes; TES charging, TES supplementing and TES discharging. During off-peak hours the cold-water production exceeds campus demand and charges the TES. During on-peak hours the TES discharges by either supplementing chiller production or meeting the entire campus cold-water demand.

*Campus demand*

Data collected from January 2009 until December 2013 with 15-min and 10 s resolution has been analyzed to evaluate and improve upon the current plant operation. The interaction between electric generators, electric chillers, cold-water storage, and the electric grid are explored to improve robustness, reliability, and efficiency without installation of additional plant hardware. The goal is to reduce operational costs by optimal application of thermal energy storage for shifting cooling demand to off-peak hours.

Measurements of campus generation, electrical imports, and chiller operation have been processed to determine the campus building's electric load. Measurements of the hot and cold water flow rates and temperatures supplied to the campus have been used to determine the campus heating and cooling loads. Measurements of ambient temperature have been aggregated to produce a single typical daily temperature profile for each month. A 2-D surface was then fit to the calculated campus demands as a function of ambient temperature and time of day. Separate surfaces were generated for weekdays and weekends/holidays due to the drastically different campus behavior. Fig. 2 presents an example of the resulting electric demand profile for an August weekday. Table 2 describes the calculated $r^2$ of these surface fits that were then used in the prediction of campus demand. Note the high correlation of cooling demand with temperature and the relatively low correlation of electricity and heating, particularly during the summer months, May–September.

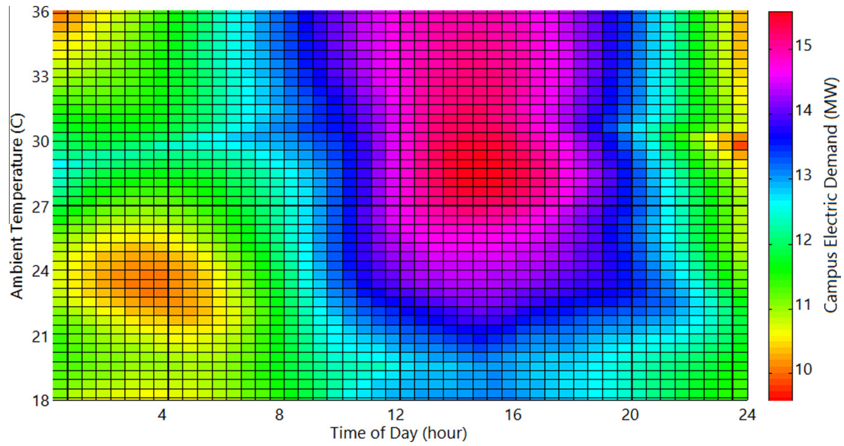


**Fig. 2.** Surface fit of UC Irvine Campus August Weekday Electric Demand.

**Table 2**
Goodness of fit for historical data as a function of time-of-day, temperature, and weekday/weekend.

| Month | Weekday | | | Weekend | | |
|---|---|---|---|---|---|---|
| | Electric | Cooling | Heating | Electric | Cooling | Heating |
| January | 0.44 | 0.87 | 0.73 | 0.33 | 0.81 | 0.50 |
| February | 0.61 | 0.82 | 0.63 | 0.57 | 0.85 | 0.61 |
| March | 0.45 | 0.80 | 0.51 | 0.26 | 0.81 | 0.33 |
| April | 0.55 | 0.61 | 0.40 | 0.48 | 0.70 | 0.44 |
| May | 0.39 | 0.89 | 0.27 | 0.33 | 0.89 | 0.21 |
| June | 0.40 | 0.84 | 0.35 | 0.44 | 0.81 | 0.28 |
| July | 0.53 | 0.84 | 0.38 | 0.32 | 0.79 | 0.23 |
| August | 0.58 | 0.86 | 0.56 | 0.42 | 0.86 | 0.43 |
| September | 0.39 | 0.85 | 0.38 | 0.28 | 0.71 | 0.37 |
| October | 0.51 | 0.81 | 0.51 | 0.48 | 0.82 | 0.42 |
| November | 0.50 | 0.83 | 0.50 | 0.43 | 0.74 | 0.49 |
| December | 0.41 | 0.64 | 0.53 | 0.32 | 0.81 | 0.47 |

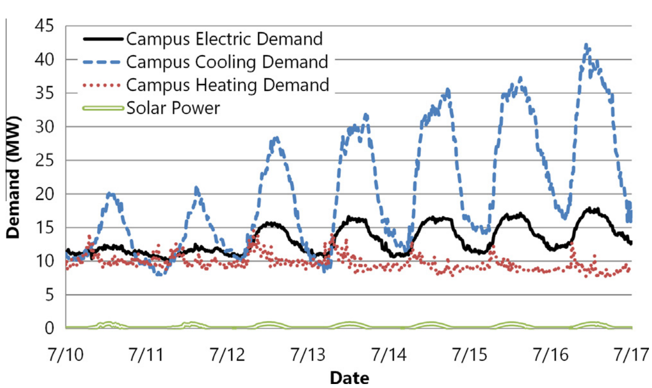


**Fig. 3.** UC Irvine Heating, Cooling, and Electrical Demands as seen by the Central Plant.

Fig. 3 summarizes the UC Irvine campus demands for a week in July, 2010. The demand for cooling clearly increases throughout the week corresponding to warmer weather. The electrical profile has two relatively flat weekend days followed by 5 weekday load profiles that also increase slightly with the warmer weather towards the end of the week. The heating demand is significantly more erratic with large morning peaks due to warming of buildings and a significant heat demand for cleaning of laboratory animal cages. The solar generation exhibits highly regular behavior during the long sunny summer days. Interviews with the plant operators have provided additional insights into the current dispatch strategy. Specific plant peculiarities observed in the data and explained by interviews with plant operators offer opportunities for improvements and motivate additional constraints that are specific to the campus plant configuration. These include turning down the steam turbine in the morning to ensure sufficient heat is available for the campus, or leaving additional chillers on as buffer against days with less than the expected cooling sea breeze. In addition, a general goal of minimizing the number of component (e.g., chiller) start-up and shut-down events is employed.

As it is currently operated the campus micro-grid is normally, but not always, an asset to the utility network. Fig. 4 illustrates how the combination of energy shifting from the TES and load following with the GT can lower and level campus electrical demand from the utility (SCE). The gas turbine follows the electrical demands of the campus except for the hottest days when campus demand is high and the TES system is insufficient to meet the entire on-peak cooling demand. On these days some chillers are operated during peak hours to supplement the TES chilling provided, adding to the daytime electric load. The combination of increased campus demand and daytime chiller operation can increase demand on the electric utility 3–5 fold and results in significant costs due to the tariff structure. Notice the high electric imports on July 13–16 shown in Fig. 4, reaching up to almost 9 MW of import on July 16 near noon. Overall, while the UCI central plant substantially reduces the overall energy use and cost to the university, manual operation and lack of a central control strategy limit the cost and emission-saving potential.

## Predictive dispatch with feedback

The first of the two optimization strategies presented is a heuristic approach that aims to mimic the manual operators' practices.

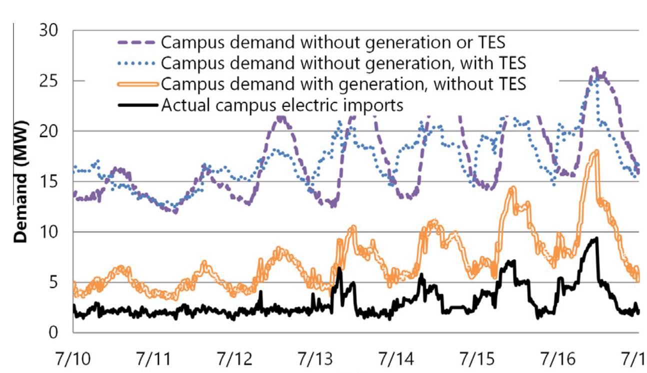


**Fig. 4.** Impact of self-generation and cold-water storage on electrical imports.

This section will first detail how the plant is dispatched for a known campus demand. Then the known demand will be replaced with a forecasted demand based upon historical data and weather forecasts. Finally a feed-back controller is added using the measured thermal storage capacity as a proxy for the error in the forecast. This strategy will be shown to improve upon the manual operator decisions due to the accuracy of prediction for campus demand, generator efficiency, and chiller dispatch.

The chiller plant dispatch focuses on two operating regimes: peak (daytime) and off-peak (nighttime). Cost savings result from utilizing the energy storage tank to shift chiller operation from peak to off-peak. Additionally, off-peak hours coincide with cooler ambient temperatures which produce colder water in the cooling towers. The colder water improves the heat transfer in the condensers, sub-cooling the refrigerant and improving the chiller plant efficiency. A chiller plant comprised of seven chillers of varying size and efficiency presents a problem with complex (and non-unique) solutions for meeting the total cooling demand. This complexity was eliminated by assuming a particular sequencing for the chillers to be brought on-line. The sequence, 7-8-5-6-1-2-3, corresponds to the manual sequencing as indicated by the plant operators. This sequence is the reverse order of the age of the chillers. Due to maintenance issues during most of the study period the steam chiller, chiller 4, is omitted from this sequence. Meeting campus demand is considered the first priority and reliability trumps the small improvement in efficiency that a different sequence might provide. The drawback to this particular sequence is that the first chillers to be started in the sequence are large. A mixed-integer optimization approach could potentially handle the complexity of multiple chillers of varying sizes and efficiencies, but may provide a solution that is at odds with practical considerations such as balancing the hours of use between chillers of different ages or avoiding excessive start-ups and shut-downs. This heuristic strategy considers plant operator knowledge and will generate dispatch scenarios that incorporate plant peculiarities, practical constraints and knowledge of the operators.

*Chiller and thermal storage dispatch*

The multi-step dispatch strategy first determines the peak and off-peak chiller plant load. It then dispatches the appropriate chillers during each period. The on-peak chiller demand is the sum of the total predicted cooling demand that occurs during on-peak hours less the capacity of the thermal storage tank. If, on a cool day, total on-peak demand is less than the thermal storage capacity, the on-peak cooling demand is zero and the tank would be charged sufficiently to meet the on-peak demand without chiller support. The tank charging occurs during the previous off-peak period and is completed before peak hours begin, 10 AM. The off-peak cooling is determined as the sum of the off-peak campus demand and the off-peak tank charging demand. Eqs. (1)–(3) outline this first step in the dispatch algorithm for shifting cooling demand to off-peak hours.

$$Cooling_{on\text{-}peak} = \sum_{on\text{-}peak} Campus\ Demand_{Cooling}\text{-}TES_{capacity} \tag{1}$$

$$TES_{charge} = min\left\{ \sum_{off\text{-}peak} (Campus\ Demand_{Cooling}) | TES_{capacity} \right\} \tag{2}$$

$$Cooling_{off\text{-}peak} = \sum_{off\text{-}peak} (Campus\ Demand_{Cooling}) + TES_{charge} \tag{3}$$

The average off-peak chiller load is this total cooling demand divided by the duration of the off-peak period. The number of chillers operated during the off-peak period, $n$, is the minimum number of chillers in the specified start sequence such that the sum of the chiller capacities is greater than the average load. This ensures sufficient charging of the TES tank will occur prior to the start of the peak period. Since the chillers are constrained to operation at or near full-load, the final chiller in the sequence is operated for only a portion of the off-peak period to ensure that the TES tank is not overcharged. All other chillers initially dispatched are operated for the duration of the off-peak period. This second step of the chiller dispatch is described in Eqs. (4)–(6).

$$Avg\ Load = \frac{Cooling_{off\text{-}peak}}{Hours\ of\ off\text{-}peak} \tag{4}$$

$$\sum_{i=0}^{n} Chiller\ Size_i > Avg\ Load \tag{5}$$

$$t_{shut\text{-}down} = \left( \frac{\sum_{i=0}^{n} Chiller\ Size_i - Avg\ Load}{Chiller\ Size_n} \right) \times Hours_{off\text{-}peak} \tag{6}$$

If the total cooling demand is greater than the cold-water storage capacity, the tank would be completely filled during off-peak hours, with the remaining on-peak demand being met in a similar fashion by the minimum number of chillers during the peak (TES supplemental mode). These chillers would remain on at the beginning of the on-peak demand period and would operate until the stored cooling could meet all of the remaining on-peak demand. The dispatch of chillers during on-peak hours is found by repeatedly solving Eqs. (4)–(6) using the on-peak cooling of Eq. (1) in Eq. (4), and the on-peak hours in Eq. (6). This strategy completely avoids chiller re-starts during peak hours and the associated problems; in-rush currents, wasted start-up energy, energy and demand charges. This approach also maximizes the continuous operation of each chiller (meeting the minimization of start-ups and shut-downs goal).

This initial automated dispatch strategy results in high peak demands and periods of non-compliance with the utility interconnect agreement. Figs. 5 and 6 illustrate the cooling demand shift and the resulting projected electric demand at this stage of the dispatch automation. Fig. 5 shows the campus cooling demand for the 5 weekdays in the same July 2010 period. Fig. 5 also shows the impact of shifting daytime cooling demand using the cold-water storage, and shows the chiller cooling generation dispatch necessary to meet the shifted cooling demand.

This initial automated dispatch of the cold-water storage has filled most of the nighttime dip in electricity demand, but results in a rather large morning peak demand as shown in Fig. 6. These results indicate that the automated chiller dispatch must be further improved to avoid excessive demand charges caused by

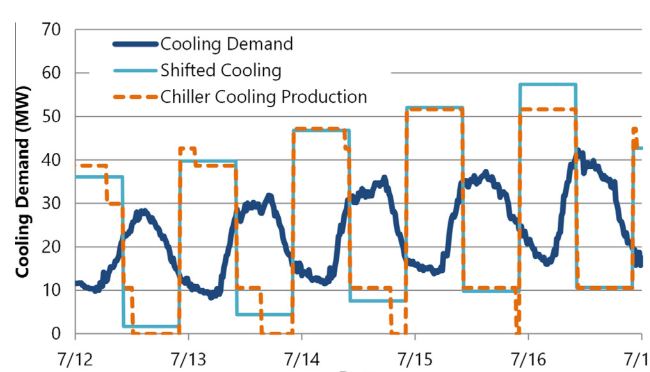


**Fig. 5.** Automated chiller dispatch with cold-water storage demand shifting.

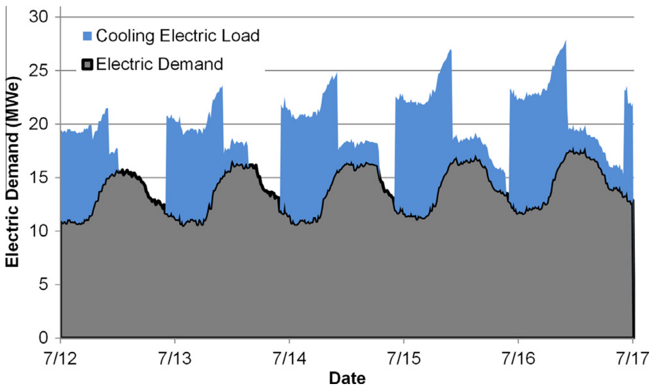


**Fig. 6.** Campus electric demand profile with forecasted electric chiller load profile for the initial automated dispatch routine.

this early morning spike in demand. The next portion of the automated dispatch algorithm reduces peak demand by shaving load that is predicted to occur during peak events. For typical daily demand profiles this step shifts morning loads of 7–10 AM to the previous evening between 10 PM and 1 AM by changing the scheduled charging of the cold-water storage.

An initial threshold is set below the peak demand and used to calculate the Reserve Capacity as per Eq. (7). The algorithm then determines the electric load of the next available chiller/s that could be met by the Reserve Capacity. An iterative solution strategy shifts cold water generation from periods of negative Reserve Capacity, hours 7–10, to the prior period with greatest positive Reserve Capacity, hours 0–2. The process is repeated with an ever lower threshold until the tank or chiller plant capacity is reached. Cold-water generation can only be shifted if the initial dispatch indicated that at least one chiller was on-line during the peak demand event of the day. Fig. 7 illustrates the calculation of Reserve Capacity for a single day, and the re-dispatch of cold water production to previous off-peak hours. With a reasonably accurate forecast of the campus demand profile, this multi-step dispatch method can closely approximate an optimized chiller plant dispatch strategy.

$$Reserve\ Capacity = Thershold + MaxGeneration - Demand \qquad (7)$$

*Gas and steam turbine dispatch*

After the chillers and thermal storage is dispatched, the expected electric load of the chiller plant is added to the campus electric load. The expected contribution of the solar generation and the minimum electricity purchase constraint are then subtracted from this net electric demand. The resulting electric load would ideally be supplied by the campus co-gen plant if sufficient capacity exists. The gas turbine is constrained to operation between 9 and 14 MW, and cannot ramp faster than 4 MW per hour. An initial guess of the gas turbine set point estimates the heat supplied to the heat recovery/steam generator which converts on average 68% of the exhaust energy into high pressure steam. The steam first supplies the campus heating load and any remaining steam drives the steam turbine. The steam turbine is constrained to operate above 750 kW to avoid the risk of an electrical trip if the campus were to suddenly draw additional steam for heating. The gas turbine power setting is adjusted until the sum of the gas turbine and steam turbine generation equals the desired co-gen production.

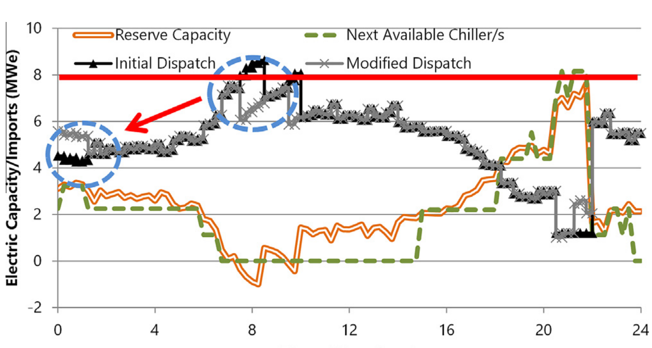


**Fig. 7.** Results of the automated dispatch algorithm with demand peak shaving for one 24 h period.

*Load forecasting & feedback*

During the initial chiller and thermal storage scheduling sufficiently accurate demand forecasts using information about recent generation levels, historical demand data, and weather predictions can substitute for precise knowledge of the actual campus demand. However, forecasted demand introduces an additional error that must be accounted for. Feedback of the actual cold-water storage tank charge level can capture both the error in plant efficiency estimates and the error in campus demand estimates. The scheduled plant dispatch and actual campus demands are applied to the simulated plant. The balance of electricity is met by the grid and the balance of cooling is met by the thermal storage. Though rarely implemented a duct burner is available to meet any campus heating not met by the heat recovery unit. This method has been implemented in a convenient graphical user interface developed in Matlab®.

The first step to each 24 h dispatch is a forecast of the ambient temperature for the next 24 h. This is done by averaging the measured ambient temperature from the previous 24 h and a historical daily temperature profile for each month. The standard deviation of the measured temperature from the historical average monthly profile of dry-bulb temperature is 2.6 °C. Combining the historical profile with the previous day's measured weather reduces the error of prediction by more than half. To avoid a discontinuity at $t = 0$ an exponential decay lasting 4 h was applied to smooth the transition from the last measured temperature to the forecasted profile. This ambient temperature prediction was then used to project the campus electric, cooling, and heating loads using the previously developed 2-D surfaces. These campus load projections were found to very well estimate the future campus demand. The generators, chillers, and thermal storage are subsequently scheduled to meet these predicted load profiles. Over the course of the next 24 h of simulated plant operation feedback from the measured capacity of the cold-water storage tank captures modeling and forecasting error, and is reincorporated into the chiller dispatch optimization at the end of each 15-min measurement interval. If the tank charged faster than expected then either the forecasted load was to high or efficiency was greater than expected, and the next scheduled chiller shut-down is accelerated to avoid over-charging the cold-water TES.

*Predictive control results*

Fig. 8 presents the predicted and actual load profiles for a single day along with the chiller dispatch strategy and water storage profile. Dashed lines are predicted values, and solid lines are the measured data. On this particular day the weather forecast over-predicted the load in the mid-day (11 AM–6 PM). Initially the tank discharges slower than anticipated. Slightly after 3 PM the control algorithm is confident that enough cooling capacity is left in the

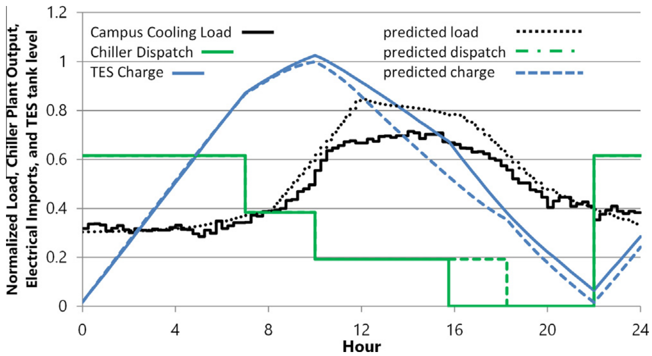


**Fig. 8.** Cooling demand and dispatch with cold-water storage for a single day (dashed lines represent predicted values, solid lines from real-time operation).

TES tank to meet the remainder of the on-peak hours without supplementary cooling from the electric chillers. At 3:30 PM the controller informs the operator that the last remaining chiller should be taken offline in the next 15 min. This corresponds to a shutdown time 2.5 h prior to the initial scheduled dispatch. During the remaining six hours of on-peak operation the TES tank empties at a faster rate than initially forecasted, but the algorithm correctly estimated that sufficient capacity remained to meet the campus demand without fully discharging the TES tank. The remaining charge in the TES tank is carried into the next day and is accounted for during the initial dispatch of chillers used to recharge the tank. This example also illustrates a slight over-charging of the TES tank occurring at 10 AM. This slight overcharging is acceptable as the tank can be cooled below its nominal 4 °C with minimal impact on the effective COP of the chiller plant.

The predictive dispatch strategy met the dynamic electric, heating, and cooling demands of the campus without exceeding the generation or cold-water storage capacity and while limiting chiller re-starts to once per day. Over the four years of study, the predictive dispatch resulted in a 22.8% reduction in electric purchases (kW h), a 1.56% reduction in net electric use (kW h), varying reductions in monthly peak energy demand (kW), slightly increased gas purchases, and a 3.61% reduction in net campus energy costs when compared to the current manual plant dispatch. The savings corresponded to a reduction in average cost of electricity from 6.52 ¢/kW h to 6.38 ¢/kW h. The average cost of electricity purchased from the utility increases from an average of 16.1 ¢/kW h to 18.3 ¢/kW h as the energy charges are reduced more than the demand charges. These costs do not include any campus plant finance or operations and maintenance costs. A summary of the financial savings is presented in Table 3. Winter months yield potential electricity purchase savings of $14,000–22,000 (6–10%), while summer months range from $50,000 to 90,000 (16–28%). The costs presented in Table 3 correspond to the projected electric utility and total charges if a predictive control strategy were implemented between 2010 and 2013. Also included is the total electric use of the campus and plant during this period. The reduction in net annual electric use (1.56%) and $CO_2$ emissions (726 Tons) stems from more efficient operation of the gas turbine and chillers, mainly by operating at night when both systems are more efficient. The emission reductions increase to 1675 tons if you consider offsetting the combustion based grid emissions at 400 g $kW^{-1}$ $h^{-1}$ instead of the renewable mix emission factor of 230 g $kW^{-1}$ $h^{-1}$.

Fig. 9 illustrates the annual variation in energy costs for UC Irvine. The predictive dispatch method is able to make greater utilization of the thermal storage capacity, and therefore results in greater savings in the summer when the size of the thermal storage becomes a constraint on plant operation. In the winter months the thermal storage capacity is more than sufficient to offset all of the on-peak cooling, and thus the manual operator dispatch matches very closely with the predictive dispatch. The operators have learned how to improve their summer performance during the period of this study. The projected electric utility savings have decreased from a maximum of 14% in 2010 to 9% in 2013. Another important way to mark this improvement in plant operation is through the percent of self-generated power. While the predictive control strategy suggests the campus plant could meet 89.1 ± .4% for each of the four years studied, the actual plant operation has increased its self-generation from 85% in 2010 to 87% in 2013.

*Impact of on-site solar generation*

During the period of study the UC Irvine campus installed 800 kW of solar photovoltaics. An additional 110 kW serves the student recreation center, which was not included in the dataset, and short-term plans call for expansion to 4 MW. The preceding predictive control strategy was repeated with 0, 1, 2 and 4 MW of installed solar capacity to evaluate the cost and emissions impact of these installations. Table 4 and Fig. 10 present a summary of the cost and emission benefits to the UC Irvine campus. The current annual emissions for the campus (including the co-gen plant and grid electricity) are 68,700 tons of $CO_2$. The co-gen plant, which only intermittently uses the steam for co-generation, averages 510 g $kW^{-1}$ $h^{-1}$ of electricity generated. The existing solar installation reduces emissions by 0.7% while supplying 1.4% of annual electricity consumption.

This difference highlights a key issue: solar installations on micro-grids may not reduce emissions as much as expected when the plant and campus dynamics are not considered. When campus demand exceeds generating capacity, the on-site solar generation reduces imported electricity and imported emissions. This occurs

**Table 3**
Electricity and fuel cost for UC Irvine central plant.

| | Electric utility ($1000's) | % Saved | Electric + Gas ($1000's) | % Saved | Electricity use (MW h) | % Saved |
|---|---|---|---|---|---|---|
| January | 202.71 | 8.1 | 688.31 | 0.59 | 10.40 | 1.93 |
| February | 189.07 | 7.6 | 635.10 | 0.20 | 9.60 | 1.43 |
| March | 201.88 | 9.4 | 678.85 | 0.60 | 10.47 | 1.72 |
| April | 196.65 | 10.1 | 657.33 | 0.85 | 10.23 | 2.33 |
| May | 221.15 | 6.3 | 704.24 | 0.81 | 11.21 | 2.95 |
| June | 231.46 | 5.3 | 688.22 | 1.41 | 10.62 | 2.23 |
| July | 242.82 | 17.7 | 723.14 | 6.12 | 11.60 | 1.10 |
| August | 243.36 | 16.6 | 732.31 | 8.89 | 12.12 | −0.62 |
| September | 228.41 | 28.4 | 696.95 | 14.93 | 11.38 | 1.00 |
| October | 231.85 | 5.7 | 722.08 | 1.79 | 11.75 | 0.07 |
| November | 196.36 | 10.1 | 657.31 | 1.93 | 10.10 | 2.72 |
| December | 187.03 | 9.6 | 653.14 | 1.57 | 9.61 | 2.34 |
| Annual total | 2572.73 | 12.0 | 8236.98 | 3.61 | 129.09 | 1.56 |

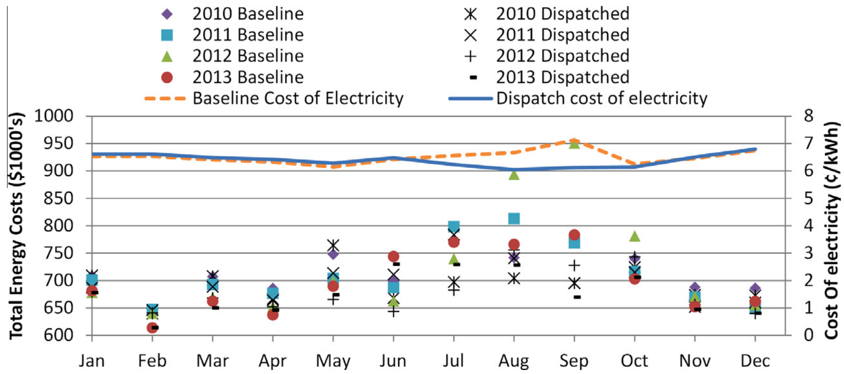


**Fig. 9.** Annual variation in UC Irvine Energy costs and comparison to predictive dispatch.

**Table 4**
Cost and emission impact of UC Irvine solar installations.

| Solar capacity | Projected annual savings ($1,000's) | Projected $CO_2$ emission savings (Tons) | Projected $CO_2$ emission savings (g $kW^{-1}$ $h^{-1}$) |
|---|---|---|---|
| 1 MW | 19.6 | 455 | 230 |
| 2 MW | 32.9 | 884 | 225 |
| 4 MW | 45.5 | 1689 | 210 |

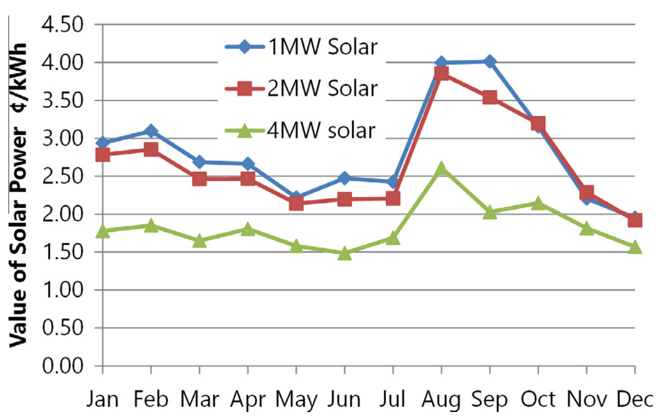


**Fig. 10.** Monthly value of solar generation to UC Irvine campus.

primarily in the summer and results in the highest value for each solar kW h generated, see Fig. 10. The remainder of the year the solar generation offsets power from the co-gen plant, causing the GT to be operated at lower power, and thus lower efficiency. With an electric demand of 10 MW, the current solar generation, 1 MW, will reduce demand on the generator by 10% while increasing the g $kW^{-1}$ $h^{-1}$ from the co-gen plant by 6.2%, resulting in a net 4.5% reduction in $CO_2$ generation. Thus when the solar power would be expected to offset 510 g $kW^{-1}$ $h^{-1}$ it is actually offsetting only 230 g $kW^{-1}$ $h^{-1}$. In California this offset emission factor is equal to the grid emission factor, but elsewhere solar power may have a considerably larger emissions impact when installed on the grid side of the fence.

Table 4 further highlights this key finding, illustrating that as the solar installation capacity increases the impact on emissions is diminished. It should be noted that although the co-gen plant emissions, 510 g $kW^{-1}$ $h^{-1}$, are higher than the average California grid emissions, the net campus emissions are lower than they would otherwise be without the campus co-gen plant due to the CHP integration offsetting the need for boilers. Fig. 10 also shows a substantial reduction in the economic value of solar generation as the installation size increases; there is little additional energy cost savings beyond 2 MW of installation. It should be noted that this analysis considers only the current campus demand and plant capacity. Future campus growth and plant upgrades may certainly realize a similar financial benefit from a 4 MW installation as is seen from the present 1 MW installation.

## Chiller dispatch optimization through linearization

The predictive dispatch strategy improved upon the manual operator dispatch, but fell short of providing a true optimized solution. For example, the peak-shaving portion of the dispatch did not consider the variable efficiency of the chillers as a function of either ambient temperature or partial-loading. Additionally, the UC Irvine campus is shifting to a direct access agreement where the electricity will be charged based upon spot prices instead of fixed rates. A formal optimization approach can incorporate and address a variety of such features. Often, the result is a nonlinear optimization problem, relying on mixed integer nonlinear programming [27,28]. Such techniques are not only computationally difficult, they might produce impractical solutions (e.g., one with numerous turn-downs and start-ups for the chillers) unless a full set of transient dynamic models are incorporated; a task that is exceedingly difficult. Incorporating penalties for chiller re-starts into the cost function of a mixed-integer program introduces additional tunable parameters and optimizes a fictitious cost that may be dominated by these extra terms.

Here, we introduce an alternative approach that relies on linear/convex optimization, which includes the influence of temperature and partial flow rate on performance and uses constraints to minimize the number of shut-downs and start-ups, while ensuring that the chillers operate at peak efficiency. For brevity, the proposed approach is introduced and its benefits are shown through an example that is simpler than the chiller plant discussed above so that the key features of the optimization are not obscured by some of the physical details of the plant. The proposed optimization directly considers ambient temperatures and humidity, campus cooling demand, linear approximations of the temperature dependence of the chiller coefficients of performance, and the cold-water storage introduced in the previous sections, as well as the variable electric rate or spot prices. Initially, the forecasted temperatures are assumed to be perfectly accurate, and the forecasted demand nearly so.

*Cost function*

The cold water plant efficiency, expressed as a COP, is the ratio of refrigeration produced to electrical consumption. The baseline net electrical cost can be described as the sum of the energy consumed for chilling multiplied by the time-of-use electrical rate for each billing segment, typically 15 min as follows

$$cost = \sum_{i=1}^{steps} \frac{Q_{c,i}(x_i) \cdot C_{energy,i}}{\mathrm{COP}_i(x_i \cdot T_i)} \tag{8}$$

where $Q_c$ is the cooling provided in kW, $C_{energy}$ is the time-varying cost of energy in \$/kW h, and COP is the composite chiller and cooling tower coefficient of performance as a function of flow rate, $x_i$ in gal/s, and wet-bulb temperature, $T_i$. The optimization decision variable is the chilling energy provided by the chiller system during each billing interval. Given the fixed temperature difference across the chillers, the instantaneous chilling power is proportional to the mass flow of water through the chillers, $x_i$. The optimization minimizes Eq. (8) subject to the chiller operation and cold-water storage tank constraints.

The specified cost function is not convex in $x$, and the constraints are non-trivial. A practical solution must be constrained to minimize start-ups to avoid system wear and demand spikes. The optimization is simplified when the operating space of the chiller plant is constrained to full-load chiller operation only. In addition to this simplification, excessive start-ups must be avoided, or else the costs and transient response considered will add to the non-linearity of this non-convex problem.

*Linearization*

Between 97% and 103% of rated capacity, the chiller efficiency varies less than 1.5%. The current linearization and optimization assumes constant COP, corresponding to the rated capacity of the chiller/cooling tower system, and develops an optimization strategy that ensures full utilization of the storage capacity. A second order polynomial closely approximates peak COP as a function of wet bulb temperature only. With this approximation Eq. (8) can be simplified to the following linear form where $f_i$ represents the known price of electricity for each interval, divided by the known chiller performance coefficient at each interval given the forecasted wet-bulb temperature. The fixed temperature differential across the chiller makes the chilling energy directly proportional to the chiller water flow. The proportionality constant is represented by $K_{chill}$ and has units of kJ/gal.

$$cost = K_{chill} \sum_{i=1}^{steps} f_i \cdot x_i \tag{9}$$

*Constraining excessive re-starts and chiller de-rate*

Beyond the obvious capacity (TES and chiller) constraints, linear constraints will address minimizing re-starts and enforcing full or near-full capacity operation of the chillers at all times. Small variations in temperature subtly change the chiller system efficiency and thus the cost of producing cold water during fixed price periods for electricity. This temperature dependence, if unaltered, dramatically affects the optimal chiller dispatch causing multiple undesirable shut-downs and re-starts. Imposing a no-start window during such periods can avoid unwarranted dispatch of chillers with a slight cooling of the weather. Limiting chiller starts to off-peak (i.e., evening and early morning) hours typically reduces the number of daily starts for an individual chiller to once per day, which is desirable and consistent with the plant operator guidelines.

The 'no increase' constraint establishes an interval during which the chilled water flow, $x_i$, only decreases or remains constant, this is best applied to peak and mid-peak price periods. In the off-peak period the reverse can be used, that is, during the off-peak period chilled water flow remains constant or increases. These inequalities (shown in Eq. (4)) constrain the optimization so that sufficient chillers are started prior to the on-peak period and that the night-time cold-water production is more evenly distributed.

$$\begin{aligned} X_i &\geqslant x_{i+1} \quad i \in \textit{no-increase interval} \\ X_{i+1} &\geqslant x_i \quad i \in \textit{no-decrease interval} \end{aligned} \tag{10}$$

Fig. 11 shows how the constraints of Eq. (10) affect the solution of the optimization problem, as the duration of the no-increase interval (shaded areas) is increased. The constraint balances the dispatch solution to avoid drastic spikes. In Fig. 11, the lower right figure shows the extreme case of implementing a no-increase constraint throughout the 24 h. In practice, of course, a combination of no-decrease (typically off-peak periods) and no-increase (peak and mid-peak periods) constraints are used to allow use of chillers after the electricity tariff is reduced.

Constraining each of the chiller's operation to at or near-full capacity requires working band constraints that limit the dispatch of each chiller to a finite range, $Q_{min} \rightarrow Q_{max}$. The span of the working bands increase as additional chillers come online. With multiple chillers each de-rating within their respective working band, a wider range of flows is achievable. Constraining the optimization solution to these working bands ensures that each chiller operates at or near full capacity. Fig. 12 illustrates the working bands for a few levels of de-rate limits. Working bands are imposed with the constraints of Eq. (11).

$$\begin{aligned} X_i &\geqslant n_i\, Q_{min} \quad \textit{lower bound} \\ X_i &\leqslant n_i\, Q_{\max} \quad \textit{upper bound} \end{aligned} \tag{11}$$

These constraints introduce an additional decision variable, the number of operating chillers, $n_i$. An iterative algorithm determines an adequate number of chillers for each dispatch interval. The initial value of operating chillers at each time interval is set to the band above the initial value of optimal dispatch solution without working-band constraints. If the maximum capacity of the cold-water storage capabilities is then violated, the initial value is reduced by one. Then the optimization is repeated for the subsequent time intervals, adding the working-band constraint one step (or multiple steps) at a time. This iterative technique is flexible to both temperature perturbations and changes in initial conditions.

*Results of the linearization technique*

Constraining the dispatch optimization with *no-increase/no-decrease* intervals prevented chiller re-starts and smoothed the chiller plant dispatch. The addition of working band constraints guarantees that the chillers operate at or near rated capacity. After a solution was obtained with the linearization, the resulting schedule was used as the initial guess to a nonlinear optimization approach (i.e. pattern search algorithm) with the full non-linear maps for COP. The results showed slight improvements, at the cost of unanticipated (and undesirable) start and/or shut down of a chiller. The difference between the two approached was about 0.7% for 95% working bands. As the range of de-rating for the chillers increase, the difference can grow as the unaccounted reduction of COP for operation in 80% or 85% rated capacity is captured by the nonlinear search (e.g., 1.9% difference for 90% working band, 4.7% difference for 80% working band). The narrow working-bands ensured operation near rated capacity and rated coefficient of performance for each individual chiller.

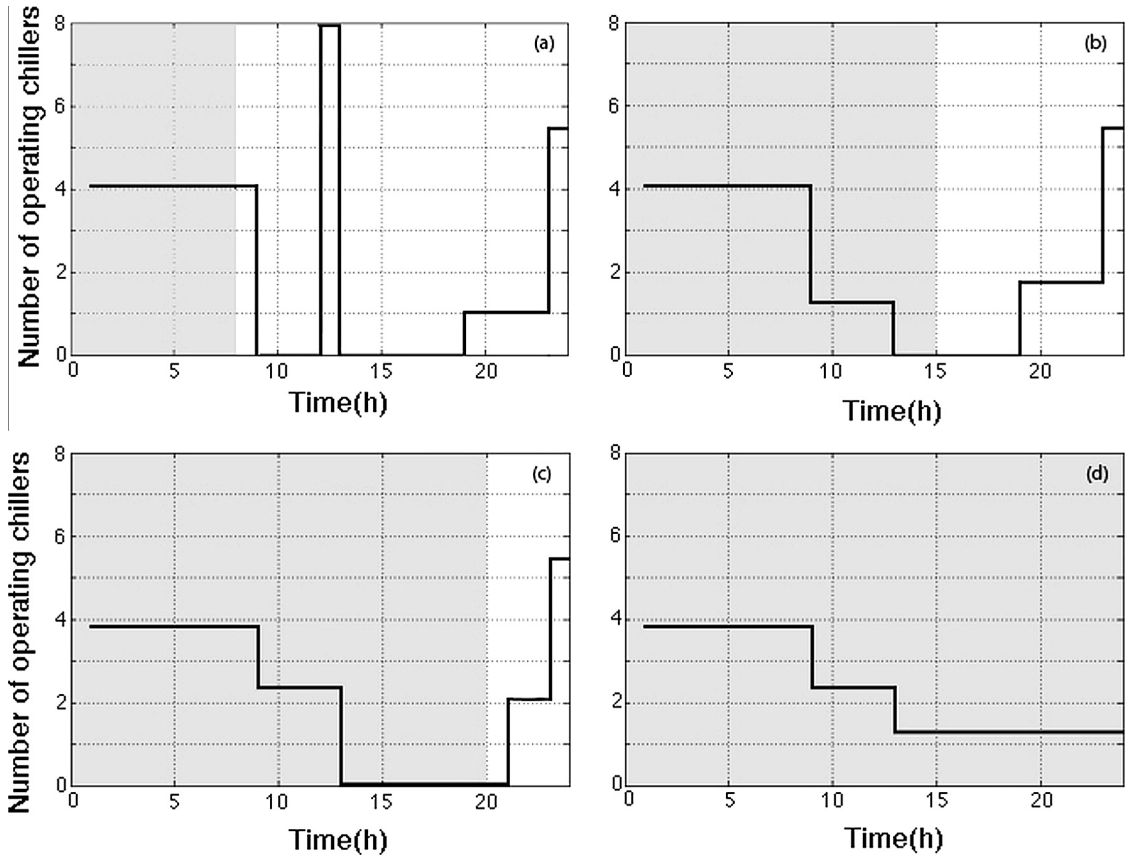


**Fig. 11.** Effects of the 'no-increase' constraints as applied to different intervals (indicated by shaded area).

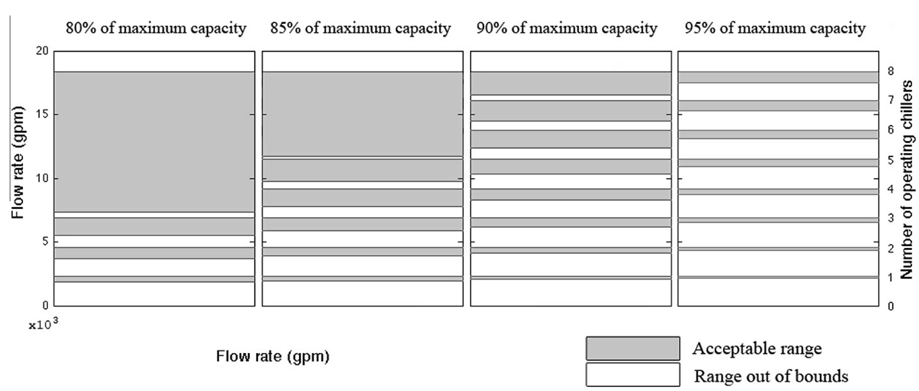


**Fig. 12.** Working bands of each chiller corresponding to different threshold limits of operation as a percentage of maximum capacity.

## Summary and conclusions

The UC Irvine campus is representative of many business, industrial, and educational campuses across the country that could benefit from self-generation, district heating/cooling, and thermal energy storage. The access to operation protocol, plant operators, and operation data enabled a detailed analysis of the plant performance with real-world considerations such as equipment maintenance and insights into campus behavior and applications that substantially affect plant operations and the load distribution. Analysis of the cold-water storage facility demonstrated that a predictive control strategy can realize substantial savings when compared to even best-practices manual operation. The combination of predictive scheduling and feedback control demonstrated potential annual electric utility bill cost savings of 12.0%, total campus energy cost savings of 3.61%, and net energy efficiency improvements of 1.56%. Emissions of $CO_2$ can be simultaneously reduced by 726 tons (1.1%); equivalent to an additional 2 MW of solar capacity.

Employing weather forecasts to predict future load profiles from historical data can provide adequate estimates for use in scheduling the dispatch of micro-grid resources, but feedback and real-time dispatch modification is necessary for effective management of energy storage resources. The greatest savings were seen during summer months due to the higher electrical rates, additional demand charges, and size constrained energy storage. The emissions reduction of solar generation on a micro-grid is highly dependent upon the campus dynamics and plant efficiency during turndown and may be considerably less than expected. There is a noticeable diminishing return on both annual energy costs and emissions reduction as the solar penetration on the micro-grid is increased.

Any predictive control strategy can be further improved with optimization, such as the linearization approach demonstrated for a chiller plant with multiple chillers and a cold-water storage tank. Working-band and no-increase/decrease constraints effectively capture real-world considerations of chiller plant efficiency and start-up limitations. Standard moving (though shrinking) horizon techniques handle any imperfect cooling demand with only one or two updates at key points (e.g., 10 a.m. and 3 p.m.). Non-uniform chiller sizes are easily addressed by adjusting the working bands and varying COPs are accommodated by turning the problem into a piece-wise linear problem (instead of linear). The techniques applied and results found in this analysis are applicable to a broad spectrum of co-located buildings generators and storage systems amenable to district heating/cooling.

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