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Cleanroom energy efficiency strategies: Modeling and simulation

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ABSTRACT

To maintain ultra-low particle concentrations, cleanrooms can require several hundred air changes per hour. These ventilation rates make cleanrooms 30–50 times more energy intensive than the average U.S. commercial building. There are an estimated 12 million m^2 of cleanroom space in the U.S., consuming over 370 PJ of energy each year. This paper explores opportunities to improve the energy efficiency of cleanrooms while maintaining or improving operating conditions.

This paper documents the modeling of a 1600 m^2 cleanroom in upstate New York. The TRNSYS model includes TMY2 weather data; building geometry and material properties; empirical data on occupancy, lighting and process equipment; and sophisticated HVAC systems. The model was validated based on metered steam, chilled water and electricity usage. Under 8% error was achieved in all fields.

Four strategies were simulated: a heat recovery system for exhaust air, resulting in an 11.4% energy reduction with a 2.7-year simple payback; solar preheating of desiccant dehumidifier regeneration air (2.4% energy reduction, 11.5-year payback); improved lighting controls (0.3% energy reduction, 1.5-year payback); and demand-controlled filtration (4.4% energy reduction, 3.1-year payback). Implementation of recommended strategies is predicted to save 9 TJ, 862 tonnes of CO_2, and $164k annually.

1. Introduction

Buildings contribute one third of global energy use and carbon dioxide emissions [1]. Cleanrooms, which can require several hundred air changes per hour through High Efficiency Particulate Air (HEPA) and Ultra Low Particulate Air (ULPA) filters to maintain low particle concentrations, are 30–50 times more energy intensive than a typical commercial building [2,3]. In 1993, the 4.2 million m^2 of U.S. cleanroom space consumed 130 PJ of energy; by 2015 these figures are expected to grow to 15.5 million m^2 and 470 PJ, respectively [4]. The potential for energy and carbon savings in cleanrooms is commensurate with the magnitude of their energy consumption.

Methods for cleanroom design and analysis were outlined by Thomas in 2005 [7], while Mills et al. presented the economic motivations for cleanroom energy efficiency in 2008 [8]. Tschudi et al. have recommended best practices for cleanroom design and operation [9], performed benchmarking surveys of U.S. cleanrooms [10], and outlined a means of using cleanroom benchmarking data to identify energy efficiency opportunities [11]. A benchmarking report on the cleanroom studied herein was performed by Mathew et al. in 2008 [12], identifying two of the energy efficiency opportunities explored in this paper.

In an effort to explore cleanroom energy efficiency strategies, the authors undertook a modeling and simulation study of a 6600 m^2 nanoscience facility. The facility was selected due to its 1600 m^2 Class 1000 cleanroom, high energy budget ($1.8 million in 2008), and comprehensive online monitoring system, which facilitated development and validation of the building model. The building consumes energy from three sources: electricity, either generated on campus or purchased from the grid; chilled water from a lake-source cooling system [5], and steam produced at a combined heat and power plant on campus [6]. Fig. 1 shows the building's electricity, chilled water and steam use by sector, according to 2008 metered data. This study focuses on the cleanroom, hereafter referred to as DHC, which consumes the majority of all three utilities.

2. Methods

2.1. Model details

In order to predict the efficacy of energy efficiency strategies, a model of DHC envelope and HVAC system was developed using TRNSYS, a transient system simulation software [13]. This software was selected due to its sophistication in dealing with complex HVAC systems, as well as the available libraries for modeling such nontraditional HVAC strategies as solar thermal heating. TRNSYS

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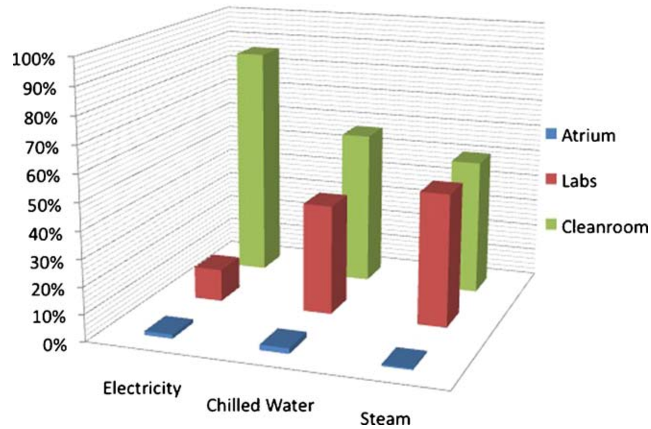

Fig. 1. Consumption of electricity, chilled water and steam by the three main building sectors.

allows the interconnection of HVAC components (either user-defined or chosen from standard libraries), and solves the resulting simultaneous system of differential and algebraic equations [14]. Fig. 2 shows the basic inputs and outputs of a TRNSYS simulation.

One input to the model is a Typical Meteorological Year Version 2 (TMY2) file, which was obtained from the National Renewable Energy Laboratory (NREL) database [15] and contains such data as dry bulb temperature, relative humidity (RH), wind speed and incident solar radiation. The remaining inputs to the model, namely building geometry and material properties, HVAC systems, occupancy, lighting, and equipment are presented in the following sections.

2.1.1. Building envelope

A model of DHC geometry was developed based on construction documents and CAD files. Because this study focused on the cleanroom, the rest of the building envelope (laboratories, atrium, and offices) was not modeled. Rather, DHC zones were considered to be adjacent to thermal reservoirs at a constant temperature of 20 °C, the setpoint to which the building's HVAC systems control hallway temperatures. Table 1 describes the thermophysical properties of the modeled wall materials.

2.1.2. HVAC system

The DHC HVAC system includes a makeup air handling unit (MAU), which filters and controls the dewpoint temperature of 1500 m^3/min of air at 6.4 °C. Conditioned air is then sent to the service area, where 25 recirculation air handling units (RAHU) re-filter and control the temperature of DHC air at 20 °C. Two fans then remove exhaust air from DHC gas cabinets and fume hoods. Positive pressure is maintained between MAU and the exhaust fans in order to prevent undesired infiltration. Fig. 3 shows the basic operation of the HVAC system.

Each HVAC unit was modeled based on data taken from the building's monitoring system. Figs. 4 and 5 compare the TRNSYS model and monitoring system representation of MAU. The TRNSYS model includes the MAU control logic and setpoints.

2.1.3. Occupancy

Occupancy schedules were developed based on empirical data taken by campus facilities staff. Table 2 shows the hourly probability of DHC occupancy by at least one person. This data was used in modeling lighting and ventilation controls, as well as internal thermal gains.

2.1.4. Lighting and equipment

Since data was unavailable for precise lighting and equipment specifications in DHC, such as peak power consumption and daily

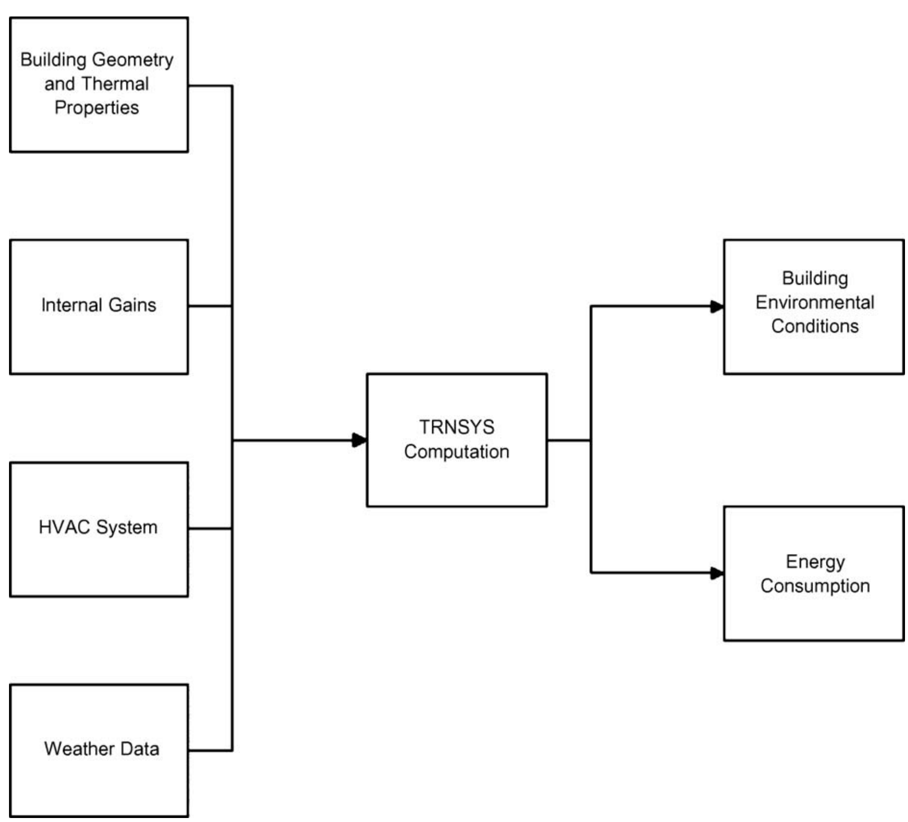

Fig. 2. Inputs and outputs of a generic TRNSYS building simulation.

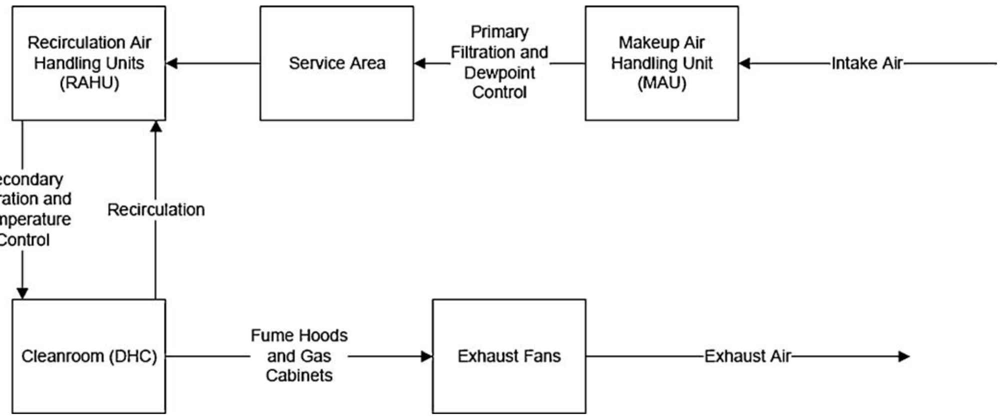

Fig. 3. Flow chart of the current DHC HVAC system.

Table 1
Thermophysical properties of DHC wall materials.

Material	Conductivity (kJ/h-m-K)	Specific Heat Capacity (kJ/kg-K)	Density (kg/m^3)
Fiberglass	0.171	0.840	12.0
Gypsum	0.580	1.090	850
Vapor barrier	–	–	Massless
Concrete	4.720	0.880	2,242
Particle board	0.125	1.250	1,000
Air space	1.129	1.020	1.20
Roof insulation	0.190	0.840	12.0
Roof membrane	–	–	Massless
Acoustic ceiling	0.206	1.250	288.3

load profiles, lighting and equipment demands were approximated as constant. Metered monthly values led to a mean equipment power intensity of 34.65 W/ft^2 (372.8 W/m^2) and lighting intensity of 1.53 W/ft^2 (16.5 W/m^2).

2.2. Model validation

Once developed, the model was checked against metered data from 2008. Although the model was quite complex, the simulated utility consumption agreed well with the metered data. Table 3 compares metered and simulated consumption values for each of the three utilities. Error was computed by the following formula: $\varepsilon = (M - S)/M$, where ε is the calculated error, M is the metered annual utility consumption, and S is the simulated annual utility consumption.

Multiple sources of error are present in building simulations. The most obvious is variation between the TMY2 dataset and the actual 2008 weather conditions. TMY2 data is compiled by selecting, for each month, the "most typical" month from the years 1961–1990 [15]. Thus, any aberrations from typical conditions that were experienced in the metered year introduced simulation error. Other errors may have been introduced by

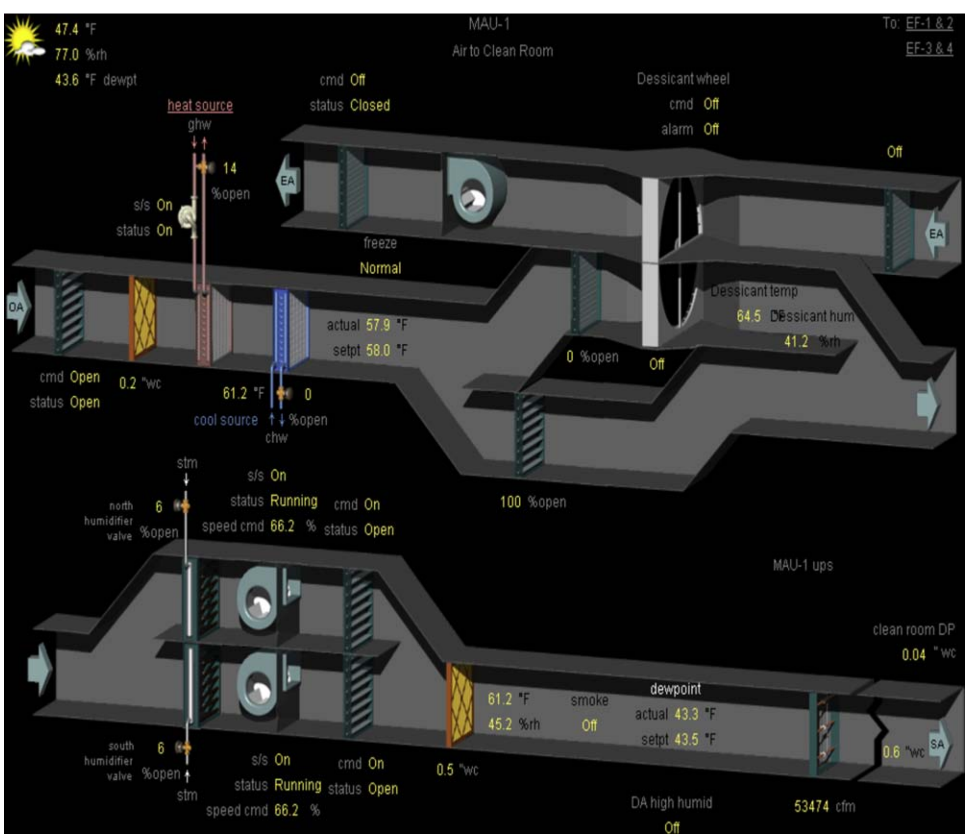

Fig. 4. Building monitoring system representation of MAU.

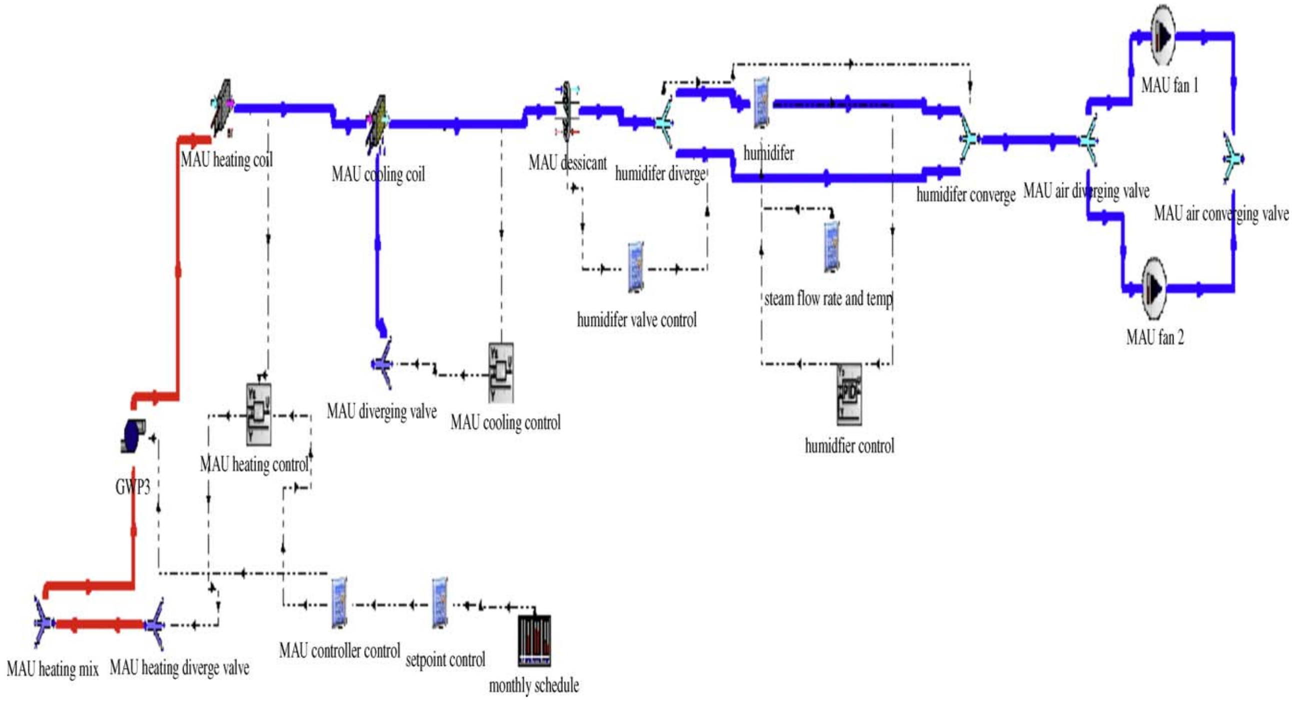

Fig. 5. TRNSYS model of MAU.

uncertainty in measurements of lighting, heating gains from process equipment and occupants, and thermophysical properties of materials. Additional sources of uncertainty in building simulation, both systematic and random, were detailed by Macdonald in 2002 [20].

Error values in the range of 4–8% are within industry standards. For instance, the ASHRAE Guideline-14 suggests that calibrated whole-building models (those where model input parameters and control systems are varied, without regard to actual building operating conditions, to reproduce measured results) should produce error values within 5% to 15% [21]. As the DHC model attempts to replicate actual building operating conditions, it was not artificially calibrated; thus, slightly higher error values are acceptable.

3. Simulated strategies

This section describes the background of and motivations for the energy efficiency strategies explored in this paper. Simulated energy savings, carbon savings, and simple payback times are calculated. Utility prices, input energy requirements, and emission rates are taken as the 2008 DHC averages, shown below in Table 4 [16].

3.1. Heat recovery system for exhaust air

Treating MAU intake air requires significant energy input, either for cooling in summer months or heating in the winter. Preconditioned air is circulated through DHC and vented to the surroundings through by two exhaust fans. At present, the preconditioning input energy is essentially wasted when the air is exhausted. A heat recovery system decreases this waste by employing heat exchangers to reuse exhaust air in the preconditioning of MAU intake air. Fig. 6 shows the DHC HVAC schematic, updated to include a HR system.

This system was modeled in TRNSYS, using an air-to-air, tube and shell heat exchanger with an effective area of 45 m^2. The

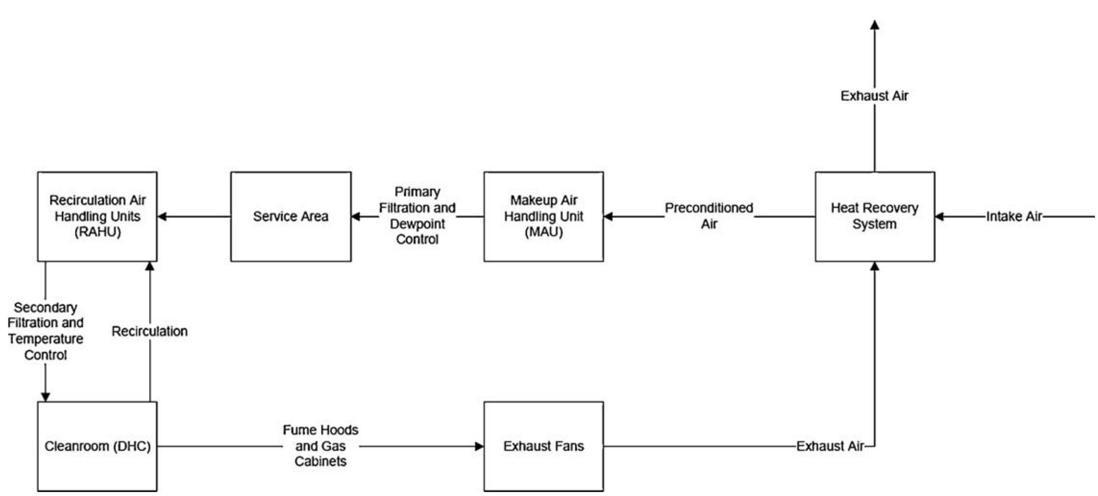

Fig. 6. Flow chart of the DHC HVAC system, updated to include a heat recovery system.

Table 2
Hourly probability of DHC occupancy.

	Hour											
	1	2	3	4	5	6	7	8	9	10	11	12
Sunday	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.25	0.25	0.50	0.50	1.00
Monday	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.25	0.25	0.50	0.50	1.00
Tuesday	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.25	0.25	0.50	0.50	1.00
Wednesday	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.25	0.25	0.50	0.50	1.00
Thursday	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.25	0.25	0.50	0.50	1.00
Friday	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.25	0.25	0.50	0.50	1.00
Saturday	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.25	0.25	0.50	0.50	1.00
	Hour											
	13	14	15	16	17	18	19	20	21	22	23	24
Sunday	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.50	0.50	0.25	0.25
Monday	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.50	0.50	0.25	0.25
Tuesday	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.50	0.50	0.25	0.25
Wednesday	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.50	0.50	0.25	0.25
Thursday	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.50	0.50	0.25	0.25
Friday	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.50	0.50	0.25	0.25
Saturday	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.50	0.50	0.25	0.25

Table 3
Model performance: simulated and metered annual utility consumption and model error.

Utility	Simulated	Metered	Error
Net electricity (GWh)	5.92	6.43	+7.9%
MAU chilled water (10^6 ton-h)	4.31	4.57	+5.7%
RAHU chilled water (10^6 ton-h)	6.13	6.39	+4.1%
MAU steam (10^6 lb)	6.77	6.28	−7.8%
Dehumidifier steam (10^6 lb)	4.78	5.06	+5.5%

Table 4
Input energy, emission rates and costs of each DHC utility.

	Steam	Chilled water	Electricity
Utility units	lb	tonne-h	kWh
Input energy per utility unit (kJ)	1,305	490.7	3,600
Emissions per utility unit (kg)	0.155	0.053	0.40
Cost per utility unit ($)	$0.021	$0.21	$0.09
2008 DHC usage (utility units)	16,441,000	1,240,592	6,428,072
2008 DHC input energy (GJ)	21,453	609	23,141
2008 DHC CO_2 emissions (tonnes)	2,543	66	2,571
2008 DHC cost ($)	$338,674	$266,727	$591,383

resulting annual steam savings were 3960 klb of steam ($81.6k). The system also saves on cooling costs in the summer; simulated annual chilled water savings were 135,500 tonne-h ($29.1k), and the total financial savings were thus $110.7k. Since the HR system is purely external, and preconditioned intake air is still subjected to MAU and RAHU conditioning, the HR system has no effect on DHC environmental conditions. At the time of construction, a heat recovery system would have cost on the order of $300k (2.7-year simple payback). However, the additional costs of retrofitting the system to the building increase the estimated total cost to $480k, and the simple payback time to 4.3 years.

3.2. *Solar thermal preheating for desiccant dehumidifier*

MAU currently employs a desiccant wheel to dehumidify intake air. The water in the intake air is absorbed by silica gel on the desiccant wheel; as the wheel spins, this water evaporates into the preheated regeneration air stream. Regeneration air is currently preheated using steam. Solar thermal preheating of regeneration air is a potential means of saving money and decreasing carbon emissions. A solar thermal system, using flat-plate solar collectors at a fixed angle, was modeled. Since winter intake air does not require humidification, the tilt angle was optimized at 38.5° for summer collection (DHC is at latitude 43.5°). In order to achieve significant energy savings, large collector areas are required. The modeled system used 500 m^2 of collector area (roughly the area of the building's roof). Simulated annual steam savings from solar thermal preheating were 834 klb ($17.4k). The modeled system cost is estimated at $200k including collectors and installation costs; the simple payback time is therefore just under 12 years.

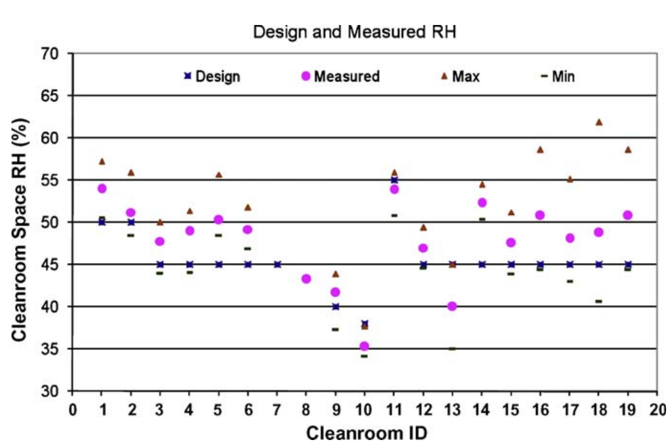

Fig. 7. Relative humidity operating ranges of cleanrooms in the LBNL benchmarking database. DHC operating range is marked by the dashed red line [12]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

3.3. Increased relative humidity setpoint

In the recently preformed benchmarking report, DHC relative humidity (RH) operating range was 37%. As shown in Fig. 7 [12], this value is significantly lower than the RH operating range for similar cleanrooms. An investigation was therefore conducted into the possibility of increasing the RH setpoint as a means of saving reheating energy.

While the building's automatic monitoring system reports RH values consistent with the 37% figure, stand-alone sensors in DHC consistently measure RH values of 41–43%. This range places DHC near the average RH of cleanrooms in the benchmarking database. Since the permissible operating range for DHC equipment is 40–45% RH, an increase in RH setpoint was deemed infeasible as it might result in damage to expensive process equipment.

3.4. Improved lighting scheduling

Fig. 8 shows the simulated electricity consumption of DHC HVAC systems, lighting and equipment. While the HVAC systems consume the majority of DHC electricity, lighting and equipment also constitute significant energy demands. The benchmarking study placed DHC process equipment power consumption on the high end of the database, suggesting potential improvements in this area; however, equipment efficiency improvements were not modeled due to inadequate precision in equipment power consumption data.

No automatic lighting control systems are currently in place in DHC. An occupancy-based control system, using the data from Table 2, was modeled. This schedule assumes full lighting during daytime hours and 20% chance of occupancy-based lighting during the low-use hours of 1:00–7:00 AM. Simulations of this control system predict a reduction in annual electricity usage of 37,000 kWh ($3.3k) with no significant impact on DHC temperature or RH conditions. Capital costs of installing occupancy-based lighting controls in DHC are estimated at $5k; the simple payback time is therefore 1.5 years.

3.5. Demand-controlled filtration

Low contaminant particle concentrations are essential to high quality cleanroom processes. In order to maintain DHC's Class 1000 particle concentration rating (fewer than 1000 particles >0.5 μm per cubic foot of air), high ventilation rates are necessary. DHC recirculation fans currently meet cleanliness standards by operating at constant speeds 24 h per day, seven days per week, regardless of contaminant particle concentration. Fig. 9 shows the operating speed of each recirculation fan as a percentage of its maximum rated speed.

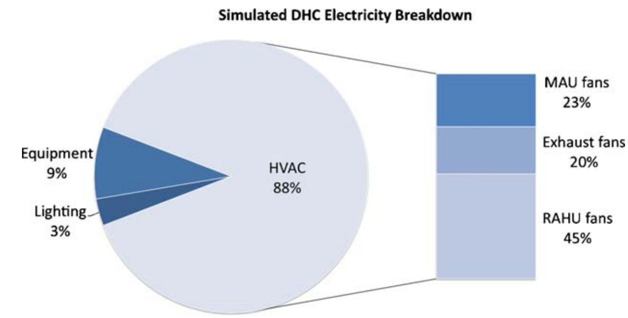

Fig. 8. Simulated DHC electricity consumption breakdown as percent of 5.92 GWh per year total.

High, constant ventilation rates may be unnecessary for maintaining desired DHC particle counts. Fig. 10 shows a typical daily particle count profile based on measurements in the scanning electron microscopy area of DHC. This profile is representative of the DHC area at large. Since the power consumption of a fan varies roughly as the cube of fan speed [17], modest reductions in fan speeds could result in significant energy savings.

A past study of demand-controlled filtration (DCF) [18] has shown 37–40% reductions in fan energy consumption when cleanroom fan speeds are modulated based on contaminant particle concentrations. In 2005, a DCF system was designed for DHC [19]; however, this system has yet to be implemented due to potential impacts on DHC environmental conditions.

DCF is typically implemented based on measurements taken either from particle counters, which employ optical sensors to sample actual contaminant particle concentrations in near real-time, or occupancy sensors. Since people are the primary source of cleanroom contamination [22], occupancy sensors provide an indirect indication of particle concentration. Past studies have shown little difference in energy savings when DCF is implemented based on particle counters or occupancy sensors [18]. Additionally, occupancy sensors are typically much less expensive than particle counters and require less maintenance. Therefore, this study focused on occupancy-based DCF as a simple and effective means of reducing recirculation fan electricity consumption.

Three overnight DCF scenarios were simulated, based on the empirical occupancy data in Table 2. In the first scenario, fan speeds were reduced from their full daytime values (Fig. 9) to 70%

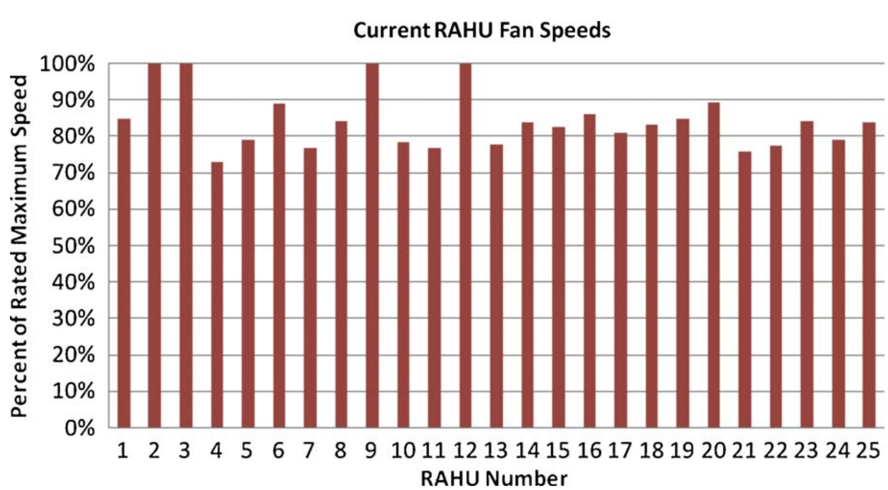

Fig. 9. Operating speeds of recirculation fans, as a percentage of their maximum speed. All fans currently operate at constant speeds.

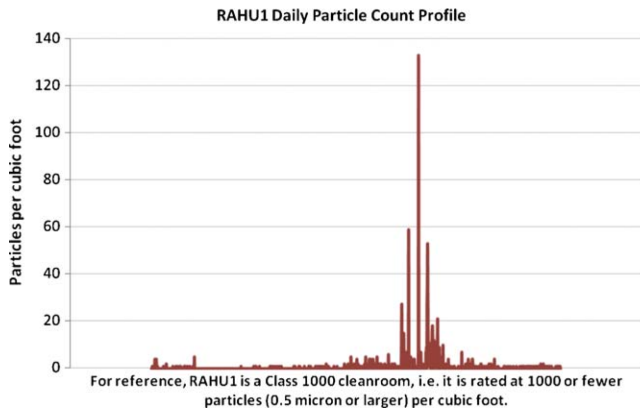

Fig. 10. Representative daily particle count profile for the zone controlled by the first recirculation air handling unit, in particles per ft^3. For reference, processes in this zone require 1000 or fewer particles per ft^3.

of that value over the course of 1 h, then maintained at 70% for the low-occupancy hours of 1:00–7:00 AM. A random variable based on occupancy probability was used in the nighttime hours to model occupancy-based fan speed increases. The second and third scenarios are similar, but reduce nighttime fan speeds to 60% and 50% of daytime values, respectively. Table 5 shows the annual electricity and financial savings of each DCF scenario.

One full-day DCF scenario was simulated for comparison. In this scenario, a random variable based on occupancy probability was used for all hours of the day. Fan speeds were gradually decreased to 50% of their current speeds (Fig. 9) when that variable was zero, i.e. during times of simulated DHC vacancy. This scenario resulted in simulated annual electricity savings of 550,000 kWh ($49.5k).

Since a particle count-based DCF system has already been installed in DHC, the cost of implementing occupancy-based DCF is reduced to labor, occupancy sensors and miscellaneous electronics. The estimated total cost is therefore $11k, and simple payback times are under 6 months for all three DCF scenarios. In the case of assembling a DCF system from scratch, the capital costs are estimated at $167k [19] and simple paybacks are 3–7 years depending on the fan speed reduction scenario employed.

4. Results

Strategies that resulted in simple payback times under 5 years were recommended for implementation. Thus, the solar thermal preheating system for MAU intake air was dismissed, although simulations suggest it would save significant amounts of energy and CO_2 emissions. Additionally, an increase in the DHC relative humidity setpoint was deemed infeasible, since it would have adverse effects on DHC process equipment. The recommended strategies, in order of ascending simple payback times, are: demand-controlled filtration, a heat recovery system for exhaust air, and improved lighting controls. Figs. 11–13 show the energy, carbon and economic impacts of the recommended strategies. The simulated net savings of the three recommended strategies amount to 9 TJ/yr (14.9%), a reduction in carbon emissions of 860 tonne/yr (16.6%), and a reduction in the total cost of energy of $164k/yr (13.7%).

Table 5
Electricity and financial savings of DCF scenarios.

Overnight reduction (%)	Electricity savings (kWh/yr)	Financial savings ($/yr)
30	240,000	21,600
40	290,000	26,100
50	350,000	31,500

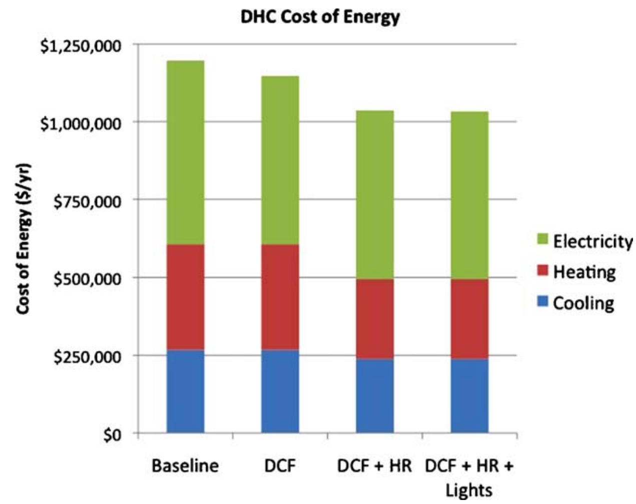

Fig. 11. Reductions in DHC energy use.

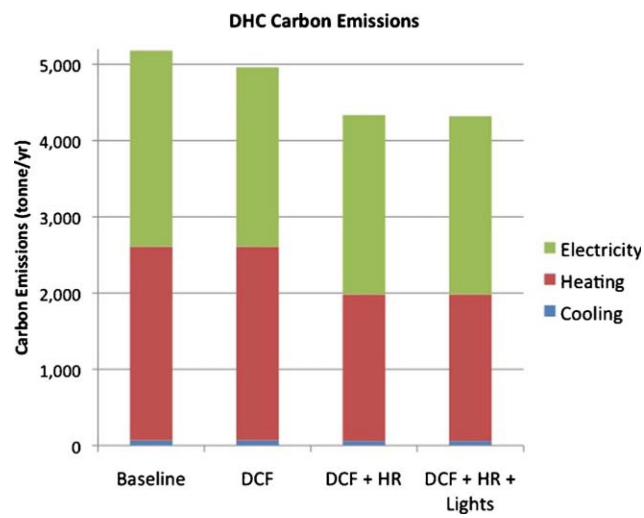

Fig. 12. Reductions in DHC carbon emissions.

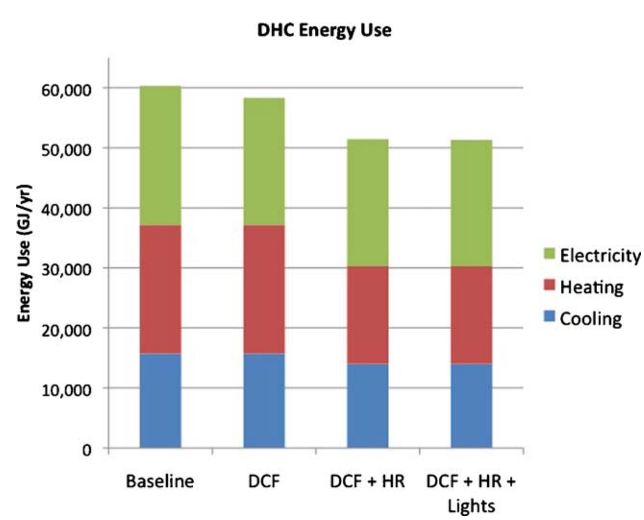

Fig. 13. Reductions in DHC energy cost.

5. Conclusions

In this study, a TRNSYS model of a large cleanroom situated within a nanoscience research facility was developed. The study aimed to identify and assess the efficacy of cleanroom energy efficiency strategies. The model was validated by comparing a full-year simulation of the cleanroom's electricity, steam and chilled water consumption with the 2008 metered values; error values of under 8% were achieved in all fields.

Once validated, the model was used to simulate the economic and environmental benefits of four cleanroom energy efficiency strategies: a heat recovery system, which uses exhaust air to precondition intake air to the makeup air handling unit; solar thermal preheating of intake air; improved lighting and equipment scheduling; and demand-controlled filtration, which modulates recirculation air handling unit fan speeds in response to varying levels of cleanroom particulate contamination. While the simulated strategies all save energy and decrease carbon emissions, they are not all economically viable. For instance, the 12-year simple payback time on the solar thermal preheating system for desiccant regeneration air is unattractive in upstate New York. However, in sunnier regions such as California and Texas (the top two states in terms of total cleanroom area), such a system would be more practical. For the purposes of this study, energy efficiency strategies with simple payback times under 5 years are considered viable.

The following strategies are recommended for DHC: full-day demand-controlled filtration (under 6-month payback), exhaust heat recovery (4.3-year payback), and improved lighting controls (1.5-year payback). Implementing all three of the recommended strategies would result in energy savings of 9 TJ/yr (14.9%), a reduction in carbon emissions of 860 tonne/yr (16.6%), and a reduction in the total cost of energy of $164k/yr (13.7%).

The energy efficiency strategies identified in this study are not only applicable to DHC, but may be generalized to cleanroom space at large. For instance, demand-controlled filtration is a little-employed strategy with great energy efficiency potential. Furthermore, this study considered only retrofit strategies; greenfield projects could employ other strategies such as improved insulation, daylighting, and (situationally) radiant cooling. If the energy efficiency of the entire U.S. cleanroom sector could be improved in line with the results of this study, significant reductions in CO_2 emissions could be achived. To wit: assuming the average carbon intensity of U.S. cleanroom space is on par with that of DHC, generalization of the strategies recommended in this paper could save on the order of 1.5 million tonnes of CO_2 emissions annually.

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