Improving the Predeveloped Local Ecology: Maximizing Condensate Collection through Strategic Building Operation

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Abstract: This work demonstrates how a water and energy sustainable building's heating, ventilation, and air conditioning (HVAC) system may be operated to maximize condensate production while upholding user thermal comfort and energy consumption requirements. A physics-based HVAC condensate model was presented and validated against operating data from the Kendeda Building for Innovative Sustainable Design (KBISD), a 3,437.4-m^2 (37,000-ft^2) academic building on the Georgia Institute of Technology's Atlanta campus. A sensitivity study of the HVAC condensate production and power consumption was performed. Metamodels were developed to concisely yet accurately represent the physics-based model, and these were used as the basis of an optimization exercise to identify competitive operating conditions for maximizing condensate production. The case studies included here found optimized HVAC system operation strategies to produce up to 708% more condensate. The demonstrated approach may be reproduced by system operators or building automation systems to increase condensate production without sacrificing building system-level energy and thermal comfort requirements. **DOI: 10.1061/JSWBAY.SWENG-476.** *© 2023 American Society of Civil Engineers.*

Practical Applications: This work demonstrates how a building's heating, ventilation, and air conditioning (HVAC) system may be operated to increase the amount of water, or condensate, which may be pulled out of the air and collected. A simple engineering model is presented and verified against real-world data. This is used as the basis for an optimization approach that allows operators to make strategic, mathematically substantiated decisions to impact the amount of condensate collected and the power required to do so. In addition, the use of so-called metamodels for reducing complex engineering models or systems into simple mathematical representations is exemplified for increasing the speed of the analyses performed in this work. These metamodels may be used to represent HVAC or other building systems and allow for optimization efforts similar to those presented herein or potentially model predictive control. The case studies discussed in this work bring the optimization approach and metamodels together to demonstrate how a building may theoretically be operated to increase its condensate production by 708% within reasonable power requirements and without sacrificing the comfort of the building's occupants.

Author keywords: Condensate recovery; HVAC systems; Net-positive energy and water buildings; Digital twin; Sustainability.

Introduction

Urban ecology is the study of the interrelationship between organisms and their physical surroundings in an urban environment. Because socioeconomic opportunity drives urbanization, with two-thirds of the global population expected to live in cities by 2050, urban ecology specifically examines the human–environment coupled system (Wu 2014). Urbanization threatens the predevelopment ecology through increased air pollution from transportation and power generation, through alterations to the local hydrology resulting in increased stormwater risk, and through the displacement of vegetation systems vital to carbon sequestration, temperature control, and habitat preservation. As cities continue expanding to accommodate population influx, urban building designers and operators will need to understand these threats to the local ecology the strategies available to help mitigate these negative impacts (Leonard and Gato-Trinidad 2020).

Urban development through building construction typically displaces local vegetation with impervious surfaces while increasing site waste production and water and energy consumption (Wu 2014; Leonard and Gato-Trinidad 2020). Regenerative buildings aim to overcome these issues by often promoting onsite agriculture, proper stormwater control, and responsible resource management, wherein resource production outweighs consumption. Regenerative energy management often integrates highly efficient construction and operation with a renewable energy source capable of generating more electricity than the building consumes. Regenerative water management similarly combines water efficient design with rainwater, fog, or condensate collecting systems to capture and use more water than

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may be otherwise demanded by the building from the local municipal water supply (Chhipi-Shrestha et al. 2018).

Building water systems may be used to improve the local ecology through improvements to site hydrology. Captured fog and rainfall can support on-site vegetation and domestic consumption. Stormwater management systems can provide stormwater sequestration and expedite groundwater infiltration (Peng et al. 2018). Condensate collected from a building's HVAC system can provide additional low-grade water for irrigation, nonpotable uses, or evaporative cooling systems. Regarding hydrological impacts on the local ecology from the construction of new buildings, rainwater collection potential is both weather dependent and fixed upon construction. However, the potential to collect condensate depends not only on weather conditions but also on the operation of a building's HVAC system. Therefore, among a building's relevant water resources, the relationship between HVAC system operation and condensate production may be leveraged to collect additional water, which if used appropriately will benefit the site's ecology.

Previous studies investigated condensate production from HVAC system operation. Algarni et al. (2018) reviewed the existing relevant literature, including the recovery of condensate and how this is estimated and the applications of the recovered condensate. Challenges facing condensate recovery were discussed, but no mention was made of system operation toward intentionally increasing condensate production. Asim et al. (2022) included condensate recovery as an important element of building HVAC sustainability but offered no technical routes to the improvement of this function. Lawrence et al. (2010) laid out a process for retrofitting existing HVAC systems for condensate collection and offered a simple calculation for determining condensate collection volume. A psychrometric process was described, and a climate-dependent condensate collection volume estimate was provided for the system's fixed design condition. This estimate considered average ambient conditions and fixed HVAC system operation (Lawrence et al. 2010). Eades (2018) investigated condensate's potential augmented role in reducing energy and water consumption in laboratory environments. A series of specific building operation strategies was explored for supplementing cooling tower make-up water with condensate, recovering HVAC system energy, and combinations of these. Optimization was not performed within these scenarios. Loveless et al. (2013) investigated the global spatial condensate collection potential. Water-scarce regions of the world were compared against potential condensate collection per ventilation rate through residential and commercial HVAC systems. Magrini et al. (2015) investigated the condensate collection potential of a hotel's HVAC system operating on the United Arab Emirates coast. This analysis used hourly ambient climate conditions and assumed a fixed delivery temperature and humidity, neglecting the opportunity for strategic building operation in condensate production.

The literature offers substantial opportunity for improving the condensate production of HVAC systems. However, substantiating an HVAC system's operation as maximizing condensate production may only be accomplished by incorporating numerical optimization into real-time HVAC operating decisions. This optimization has not been presented in the literature. Furthermore, the operation of HVAC systems with competing objectives of maximizing condensate production and preserving both thermal comfort and building system-level energy objectives has not been rigorously considered. This latter consideration is becoming increasingly relevant as sustainable or regenerative buildings seek environmental certification in greater and greater numbers (ILFI 2022). Therefore, this work aims to investigate how a building's HVAC system may be operated to maximize condensate production while upholding user thermal comfort and energy consumption requirements. The condensate module of a digital twin developed alongside the Georgia Institute of Technology's Kendeda Building for Innovative Sustainable Design (KBISD), located in Atlanta, will be used as a case study to exemplify the presented approach. More information on this building and the construction of its digital twin is available in the literature (Brooks et al. 2021; Lewe et al. 2022). The presented condensate module, verified against data from remote instrumentation online within KBISD, will quantify the condensate production potential under a few practical case studies.

Methods

This work aims to investigate HVAC system operation for maximizing condensate production. Fig. 1 shows the method pursued in the present work to accomplish this and serves as a guide to ground the following sections of the article. Arrows represent the flow of information, such as operating data, produced condensate, consumed power, and operating controls, moving from left to right in Fig. 1. To control condensate production without sacrificing other building requirements, the relationship between condensate collection, power consumption, and the thermodynamic properties of the conditioned airstream must be characterized using physics-based models or actual operating data. This relationship, if complex, may then be represented by metamodels for high-speed use in subsequent analyses and control strategies. Metamodels are simple mathematical representations used to approximate complex models in cases where low computational expense is more important than the fidelity of the result. These metamodels may be constructed and then used as the subject of an optimization exercise to determine hourly operating strategies for maximizing condensate production within the HVAC system's power budget and other constraints. Note, in cases where a simple closed-form mathematical model is available for capturing condensate production and power consumption accurately, such as in this work, metamodels may not add significant value. This work includes metamodels to exemplify how they may be used in cases where more complex systems require data-driven or more complex models.

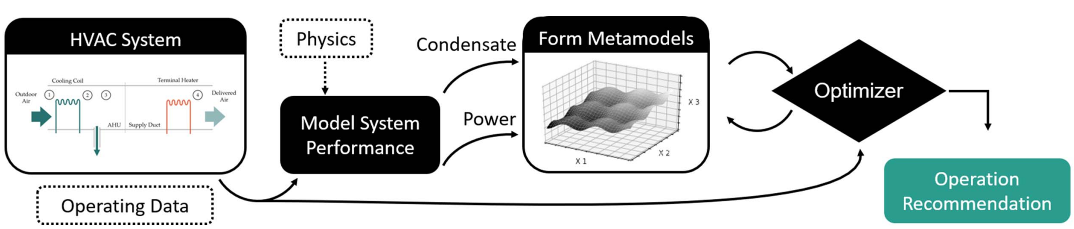

Fig. 1. Method pursued in this work for maximizing HVAC system condensate production.

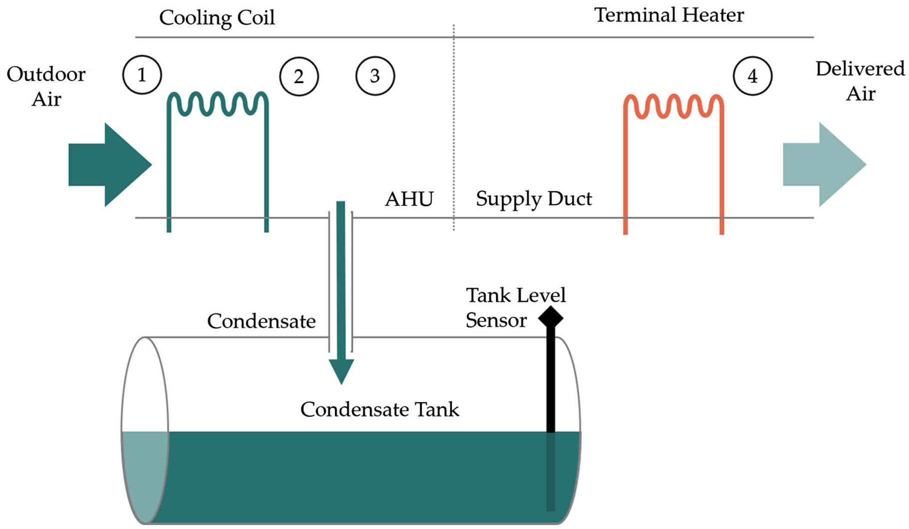

Fig. 2. Condensate collection system consisting of an air handling unit and a condensate collection tank.

Estimating Condensate Collection

Building HVAC systems may be used to cool moist air and remove any associated condensation. Buildings that collect condensate may measure the collection rate through the careful installation of flow meters or through sensors that measure the collection tank's water level or weight so long as all other inflows and outflows are also measured. Buildings that do not specifically measure condensate collection but aim to understand the amount of condensate collected must estimate this using a physics-based model. To understand and leverage the underlying physics of the dehumidification process, a psychrometric model was constructed in this study. The HVAC system underpinning this model is depicted in Fig. 2. The system is very simple but represents well the relevant cooling and reheating function of the actual system used for the model's validation and the two optimization case studies, while neglecting components that are functionally irrelevant to this work. An air handling unit (AHU) consisting of a cooling coil is used to cool the air and remove water where applicable. Terminal heaters are located downstream of the AHU for reheating the air when necessary.

The developed model assumes that the AHU is used for dehumidification and cooling only. It is also assumed that the air behaves as an ideal gas and that no condensate losses occur between the AHU and the condensate tank. The AHU delivers moist air volumetric flows up to 5,191 L/s (11,000 cfm). The delivered air mass flow is determined using Eq. (1), as follows:

$$\dot{m}_{\mathrm{air}_1} = \dot{m}_{\mathrm{air}_3} = \dot{m}_{\mathrm{air}} = \frac{P_{\mathrm{atm}} \dot{V}_{\mathrm{air}}}{R_{\mathrm{air}} T_{\mathrm{air}}} \tag{1}$$

where $\dot{V}$ (m^3/s) = volumetric flow; P (Pa) = air pressure; R (kJ/kg × K) = specific gas constant of air; and T (K) = air temperature. The humidity ratio, the mass ratio of water vapor to dry air in the moist air stream, at each location within the AHU is found using Eq. (2), where P_{sat} (Pa) is the saturation pressure and Ø (%) the relative humidity of the air at temperature T (°C) found using Eq. (3). Eq. (3) drives system nonlinearity and was formed from thermophysical property data (Moran et al. 2010)

$$\omega = 0.622 \left(\frac{\text{Ø} P_{\mathrm{sat}}}{P - \text{Ø} P_{\mathrm{sat}}} \right) \tag{2}$$

$$P_{\mathrm{sat}} = 6.17024 \times 10^{-2} T_{\mathrm{air}}^3 + 4.15 \times 10^{-1} T_{\mathrm{air}}^2 + 54 \times T_{\mathrm{air}} + 591.5 \tag{3}$$

The collected condensate mass flow, $\dot{m}$ (kg/s), is computed by taking the difference between the humidity ratio of the outgoing and incoming air using Eq. (4) as follows:

$$\dot{m}_{\mathrm{condensate}} = \dot{m}_{\mathrm{vapor}_1} - \dot{m}_{\mathrm{vapor}_3} = \dot{m}_{\mathrm{air}} (\omega_1 - \omega_3) \tag{4}$$

The performance of the AHU in delivering condensate may be determined using the simple foregoing equations. The rate at which heat is withdrawn to produce cooler and drier air may be found using Eq. (5), where h (kJ/kg) is the specific enthalpy of the air, vapor, and condensate in the form of a saturated liquid.

$$\dot{Q}_{\mathrm{Out}} = \dot{m}_{\mathrm{air}} [(h_{\mathrm{air}_3} - h_{\mathrm{air}_1}) - \omega_1 \times h_{\mathrm{vapor}_1} - \omega_3 \times h_{\mathrm{vapor}_3} + (\omega_1 - \omega_3) h_{\mathrm{SatLiq}_3}] \tag{5}$$

To deliver a specific relative humidity with a lower humidity ratio across the AHU, the outdoor air is cooled until it becomes saturated (Ø = 100%). Condensate is then removed until the specific humidity ratio is achieved before the air is reheated to the desired delivery temperature by the terminal heaters in this work. The rate at which air is heated after condensate is removed may be found as follows using Eq. (6):

$$\dot{Q}_{\mathrm{In}} = \dot{m}_{\mathrm{air}} [(h_{\mathrm{air}_4} - h_{\mathrm{air}_3}) + \omega_3 (h_{\mathrm{vapor}_4} - h_{\mathrm{vapor}_3})] \tag{6}$$

The power required, $\dot{W}(kW)$, to operate the AHU and terminal heaters in a specific way depends upon the incoming and delivered airstreams as well as the system's ventilation rate. This relationship is shown in Eq. (7), where the coefficients of performance, $\mathrm{COP}_{\mathrm{Ref}}$ and $\mathrm{COP}_{\mathrm{HP}}$, relate power required to the rate of heat removal and heat addition, respectively. Note that $\mathrm{COP}_{\mathrm{Ref}}$ here needs to include the entire cooling system power required, including interactions with chilled water or other sophisticated systems

$$\dot{W} = \frac{\dot{Q}_{\mathrm{Out}}}{\mathrm{COP}_{\mathrm{Ref}}} + \frac{\dot{Q}_{\mathrm{In}}}{\mathrm{COP}_{\mathrm{HP}}} \tag{7}$$

Verifying Condensate Collection Model

The Georgia Institute of Technology recently added the KBISD, a 3,437.4-m^2 (37,000-ft^2) academic building, to its Atlanta campus. KBISD has received the International Living Future Institute's Living Building Challenge certification for its performance in minimizing waste and life cycle carbon emissions while generating more electricity than it uses annually and harvesting more rainwater and condensate than it consumes. A digital twin of KBISD was constructed and used to verify and project building performance, monitor functional changes, and advise building operators (Lewe et al. 2022). This digital twin relies on a network of remote instrumentation that monitors much of the mechanical, electrical, and plumbing equipment as well as the large data stream accompanying these. The condensate model used in this work was incorporated into this digital twin.

Actual building operational data from KBISD were used to verify the discussed condensate model. Fig. 2 represents well the cooling function of the KBISD condensate recovery system as relevant to this work. Additional systems, including a heat recovery wheel and the potential for air recycling, exist in the actual KBISD HVAC assembly, but these are not used during model validation or the proposed cooling operation explored in the hypothetical case studies considered and are therefore not modeled here. This simplification means that opportunities for power savings may be sacrificed to maximize condensate production. The case studies in the results section address this issue by constraining the power consumption of the system while maximizing condensate production. Two AHUs within the building are used in the summer to cool air to a desired temperature and humidity. In this process, water is removed from the moist air and directed toward a 4,542-L (1,200-gal.) collection tank. Note that KBISD's HVAC systems operate on Georgia Tech's district cooling network. Therefore, condensate collected by cooling air at the building may be outpaced by evaporative cooling water consumption attributed to recooling the district cooling network's water at the central chiller plant. True water savings at the overall system level may therefore be improved using an air-cooled condenser or nonconsumptive dry cooling. In addition, operating on a district cooling network may make accomplishing the cooling required to maximize condensate difficult because the chilled water temperature is fairly fixed and the flexibility in available water flow may be limited.

No flow meters are installed for measuring the inflow of condensate directly. However, a water level sensor with an accuracy of ± 1.2 mm (0.048 in.) is installed vertically within the horizontal cylindrical tank. Within the 1.2-m (48-in.) diameter tank, the water level sensor, in the absence of additional inflows or outflows, estimates the volume of the tank with an average accuracy of approximately ± 7.6 L (2 gal.). Fig. 3 shows the KBISD measured and model estimated hourly condensate collection from (1) June 2–5, 2020, and (2) August 16–25, 2020. These two operating periods were selected because they exhibit the cooling operation, which is of interest in this work, namely large amounts of condensate production and no heating. The modeled condensate production matched well both in the magnitude and trend of the measured data across operating and nonoperating hours. The mean absolute hourly error was found to be 3.94 and 4.01 L across each period, respectively. This is well below the average error of the tank level instrumentation itself, suggesting the condensate model captures well the physics of the actual system and will be sufficient for use in this work.

Condensate Collection Sensitivity

If building operators are able to determine the impact of AHU operating settings on delivered condensate and power consumption, they may leverage this to operate the building in more advantageous ways regarding each. A sensitivity study was performed to map AHU operating parameters to both condensate production and required power using the statistical software JMP (Jones and Sall 2011). To do this, the condensate model was used across a 3,883 case design of experiments (DoE). The results obtained from this DoE were used to determine both the impact on the variability of each response and the response sensitivity of each of the AHU operating parameters. Fig. 4 presents a rank ordering of variability in response for both (1) condensate collection and (2) power required. Here, the contribution portion to the variability of each response due to each input variable is plotted against the input variables themselves. Airflow rate, outside air temperature, and outside air humidity dominate condensate collection, contributing approximately 39%, 28%, and 24% of the weight in the condensate collection variability, respectively. Similarly, approximately 84% of the weight in power required variability is also contributed by these three variables, though it is notable that delivered air humidity (DAH) outweighs outside air humidity here. Because only delivered air qualities, those just after the AHU here, may be used to control the HVAC system, this sensitivity study informs their order of impact on both condensate collection and power as airflow, then humidity, and, finally, temperature. Because none of these three is insignificant with respect to the system's responses, all three should be included when formulating an operational strategy.

Fig. 5 shows the sensitivity of both condensate collection and power required to the five considered input parameters. These profiles are a direct result of the DoE wherein condensate collection

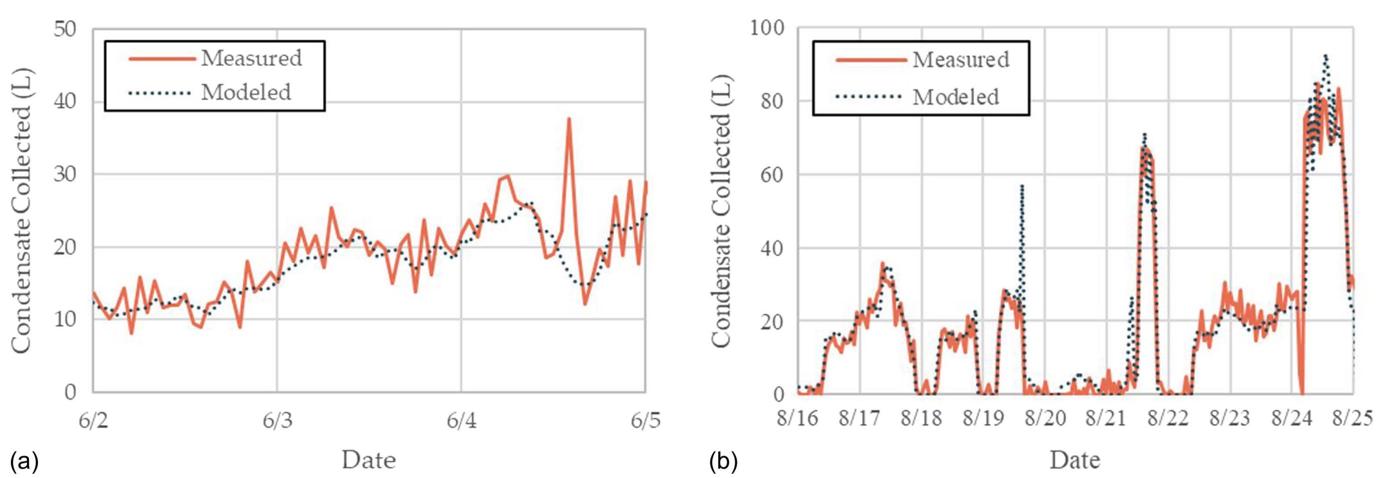

Fig. 3. Verification of condensate collection model using KBISD operating period: (a) June 2–5, 2020; and (b) August 16–25, 2020.

Predictor	Condensate Collected (L/h) Contribution	Portion	Rank	Power Required (kW) Contribution	Portion	Rank
Outside Air Temperature (C)	793363	0.2808	2	97820	0.1874	2
Outside Air Humidity (%)	675508	0.2391	3	43851	0.0840	4
Airflow (L/s)	1106391	0.3916	1	295629	0.5664	1
Delivered Air Temperature (C)	64253	0.0227	5	11838	0.0227	5
Delivered Air Humidity (%)	185929	0.0658	4	72813	0.1395	3

(a) (b)

Fig. 4. Rank ordering of each operating parameter regarding impact to response variability for (a) condensate collected; and (b) power required.

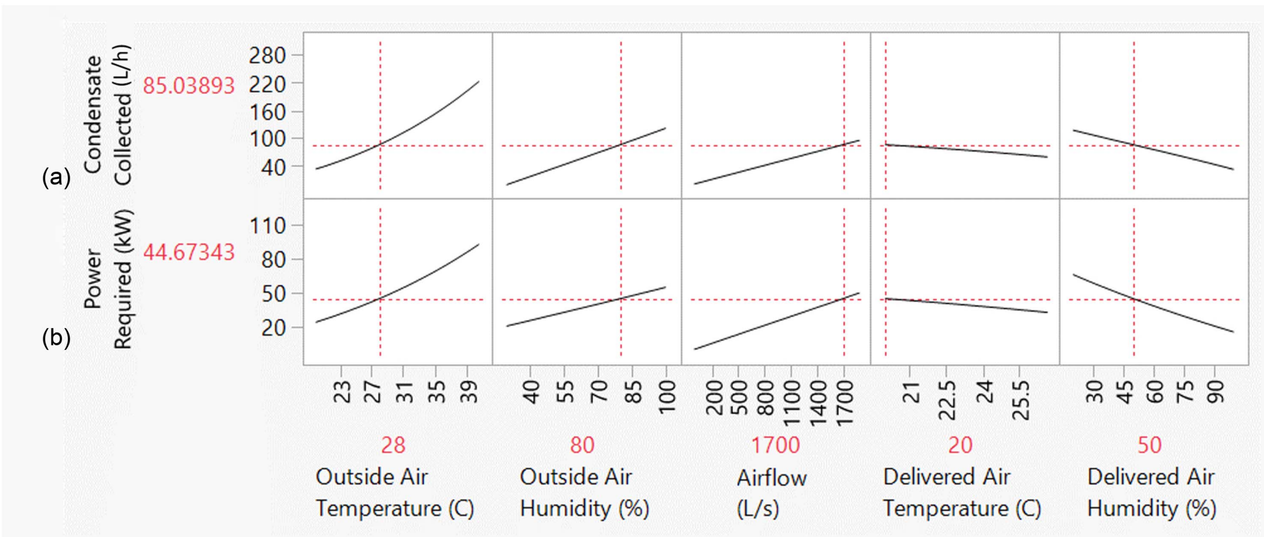

Fig. 5. Sensitivity profiles for each operating parameter regarding impact to response for (a) condensate collected; and (b) power required.

and power consumption were estimated as functions of the five input parameters using the introduced model and confirm the overarching trend that condensate collection correlates with power consumption. Among these, power consumption and condensate collection are proportional to outdoor air qualities and delivered airflow and inversely proportional to delivered air temperature (DAT) and DAH. For each of the control values, the slope of each profile suggests that increasing the airflow rate will deliver more condensate while requiring more power than decreasing the delivered humidity by the same percentage. Decreasing delivered humidity outweighs both the cost and benefit of decreasing the temperature by the same percentage. These align with the conclusions drawn from the variability rankings of Fig. 4. Numerical optimization is needed to determine the AHU operating setting that maximizes the amount of condensate produced for a given power allowance.

Optimization for Maximizing Condensate Collection

This work aims to demonstrate the improved condensate collection potential of condensate collecting buildings. Specifically, it is of interest to determine how a building's HVAC system may be operated to produce additional condensate while maintaining thermal comfort. The introduced physics-based model has proven adequate for characterizing the relationship between condensate production, energy consumption, and HVAC operation. More complex models may be able to better capture this relationship, but at the cost of computational expense, which adds difficulty when incorporating these into an optimization scheme. To avoid this, metamodels, which are simple mathematical representations used to approximate complex models, may be introduced. This work uses artificial neural networks with 20 nodes of the form of Eqs. (8) and (9) to estimate condensate collection, $\dot{m}$ (kg/s), and power required, $\dot{W}\,(kW)$. Metamodels are used to exemplify their application to more complex HVAC systems or in cases where data-driven models may be necessary. The models used in this work are simple and do not themselves require metamodels.

$$\dot{m}_{\text{condensate}} = \dot{m}_{\text{air}} \times \left[a + \sum_{i=1}^{20} b_i \times \tanh(0.5 \times (c_i + d_i \times \text{OAT} + e_i \times \text{OAH} + f_i \times \text{DAT} + g_i \times \text{DAH}))\right] \tag{8}$$

$$\dot{W} = \dot{m}_{\text{air}} \times \left[a + \sum_{i=1}^{20} b_i \times \tanh(0.5 \times (c_i + d_i \times \text{OAT} + e_i \times \text{OAH} + f_i \times \text{DAT} + g_i \times \text{DAH}))\right] \tag{9}$$

The introduced metamodels, of the form of Eqs. (8) and (9), were constructed using a neural net fitting tool in JMP (Jones and Sall 2011). Twenty hyperbolic tangent nodes were selected to form Eqs. (8) and (9) because these produced the strongest fit results,

Table 1. Inputs, outputs, constraints, and objective function used in this work

Parameter	Type	Minimum	Maximum	Unit
	Inputs			
Outdoor/delivered airflow (OAF)	Constraint	0	5,191.4	L/s
Outdoor air temperature (OAT)	Historical data—hourly fixed	20	40.6	°C
Outdoor air relative humidity (OAH)	Historical data—hourly fixed	30	100.0	%
Delivered air temperature (DAT)	Constraint	20	26.7	°C
Delivered air relative humidity (DAH)	Constraint	20	100.0	%
	Outputs			
Condensate collected	Objective function—maximize	0	190.0	L/h
Power required	Constraint	0	20.0	kW

regarding the coefficient of determination. A range of other node counts for both linear and Gaussian forms were also considered, with less successful outcomes. The two selected models were trained using 80% of the data, randomly selected by case, from the same DoE as was used in the sensitivity study. However, to isolate the impact of the thermodynamic conditioning of the air, each case was normalized by its incoming airflow. Eqs. (8) and (9) performed exceptionally well when the airflow was removed from the training data and reintroduced to scale the surrogates themselves. Extrapolation beyond the normal practical operating window of 0–1,888 L/s, up to the operating limit of 5,191.4 L/s, is considered appropriate here based on the linear airflow dependence of the system. Should the system performance change dramatically above 1,888 L/s, the results of the case studies below will change, but the presented optimization approach may still be used and improved with a more appropriate model. The remaining 20% of the data from the DoE was used for verification. This data split of 80% training to 20% verification reflects common practice and aims to provide enough training data to minimize model variance in formation while preserving enough verification data to allow for an unbiased and statistically relevant model assessment. The metamodels exhibited a coefficient of determination in excess of 0.999 compared to both training and verification data.

Optimization relies on the rapid execution of the subject analysis in order to identify competitive combinations of input parameters. The developed metamodels allow for optimization exercises to be performed. A sequential least squares (SLSQP) optimization algorithm was selected from SciPy's Optimize package because it offers a quick and suitable option for this nonlinear constrained problem. For a given set of outdoor air temperature and humidity and subject to thermal comfort temperature and energy availability constraints, this open-source optimization algorithm may be used to provide a locally optimal selection of delivered airflow, temperature, and relative humidity for maximizing condensate production. Table 1 summarizes the inputs, outputs, objective function, and constraints employed in this effort.

Results

Numerical optimization was used to determine the AHU operating settings that maximized condensate production for a given power allowance. KBISD served as an example building constructed in a growing urban area. Note that the simplified model introduced here was used to estimate condensate production in these hypothetical case studies and neglects a few of KBISD's actual systems, such as the heat recovery wheel, as explained previously. Hourly power allowances were considered in the context of the building's sustainability targets. In 2020, KBISD generated approximately 123% more electricity than it consumed (Lewe et al. 2022). The condensate model, with operating points aligned with thermal comfort constraints, estimates KBISD to have collected 19,082 L of water from HVAC condensate over the same time period. The simulated performance of KBISD in 2020 will be considered the baseline case in the following two case studies. Hourly outdoor air temperature and humidity, as well as the actual power production and consumption of KBISD as measured by the building, are used.

Case 1: Building Energy Performance Preserved

To preserve the net energy performance of the building, it is of interest to determine how much condensate may have been produced in 2020 without sacrificing any of the net positive electricity production. Hourly HVAC parameters from the baseline case were used alongside Eqs. (5) and (6) to estimate HVAC-specific power consumption. Because the model considers primarily cooling for condensate collection, HVAC operation between April and September are considered here. For every hour within this 6-month period, optimization was performed wherein condensate collection was maximized without consuming more power than was originally consumed in the baseline case. To maintain thermal comfort, the minimum DAT was constrained to between 20°C and 26.7°C per the US Centers for Disease Control and Prevention's (CDC) recommendation (CDC 2022). Also, the minimum delivered air relative humidity was constrained to greater than 20%, and mixing with existing room air upon delivery will occur (IDPH 2022). The maximum ventilation rate was constrained to 5,191.4 L/s, per the design operating capacity of the installed system. Discomfort from operation at maximum airflow due to noise or perceived draft is not considered here. The non-HVAC power demand of the building was preserved.

Fig. 6 shows the condensate collection, power consumption, and selected delivery airflow, temperature, and humidity for a 1-week period in June. By operating at a lower delivery humidity within the comfortable temperature bounds, the building was estimated to have collected 20,532 L of condensate in 2020, or 8% improvement over the baseline case. In periods where the condensate production is improved over the baseline case, the airflow is lowered to a ventilating flow to save power. This saved power is used instead to lower the air's humidity, yielding additional condensate. In this period, the temperature is consistently delivered at its minimum allowable value of 20°C, where thermal comfort is maintained and condensate collection is maximized. Given the thermal comfort constraints applied in this work, the baseline building operation is producing nearly the maximum amount of condensate for its allotted power budget. Still, optimization allowed for an additional 8% improvement in condensate production for the same amount of power.

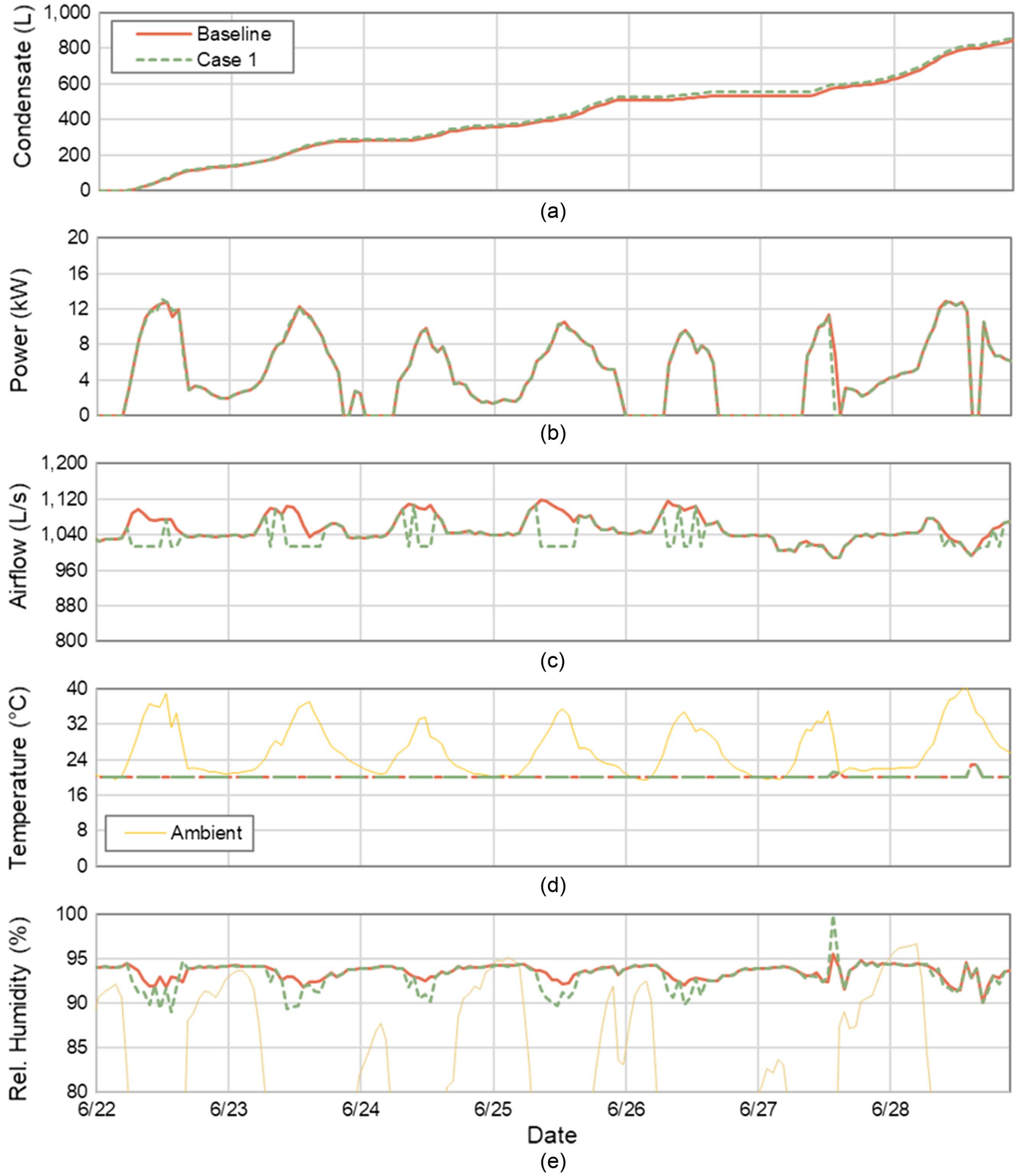

Fig. 6. Comparison of baseline case and Case 1 for (a) condensate collection; (b) power consumption, delivered (c) airflow; (d) temperature; and (e) relative humidity.

Case 2: Building Condensate Production Maximized

To determine the ecological potential of the building's condensate collection, Case 2 investigates the additional condensate recovery that may be achieved if excess power generated from the building is directed toward this purpose. Because electrical storage on a building scale is expensive, and considering the grid supply and demand obstacles facing solar arrays, redirecting excess power toward condensate production may offer net ecological benefits. Case 2 considers an hourly power allowance collection that preserves a net annual positivity of 50%, diverting about 40% of its otherwise available excess power to condensate production. The optimization approach used in Case 1 is reapplied to Case 2, maintaining all assumptions and thermal comfort constraints and considering the augmented hourly power allowance set.

Fig. 7 shows the condensate collection, power consumption, and selected delivery airflow, temperature, and humidity for a 1-week period in June. The increased hourly power allowance enables the HVAC system to be operated at a significantly lower humidity and at an increased airflow rate compared to both the baseline case and Case 1. Again, the temperature is consistently delivered at its minimum allowable value of 20°C, where thermal comfort is maintained and condensate collection is maximized. In Case 2, the building is estimated to have collected 154,214 L of condensate in 2020. This is a 708% improvement over the baseline case enabled by a redirection of 40% of the building's excess energy and, more importantly, strategic HVAC system operation. The results of all three cases are summarized in Table 2.

This work assumes that the system outside airflow capacity of 5,191.4 L/s is an acceptable operating condition for the comfort

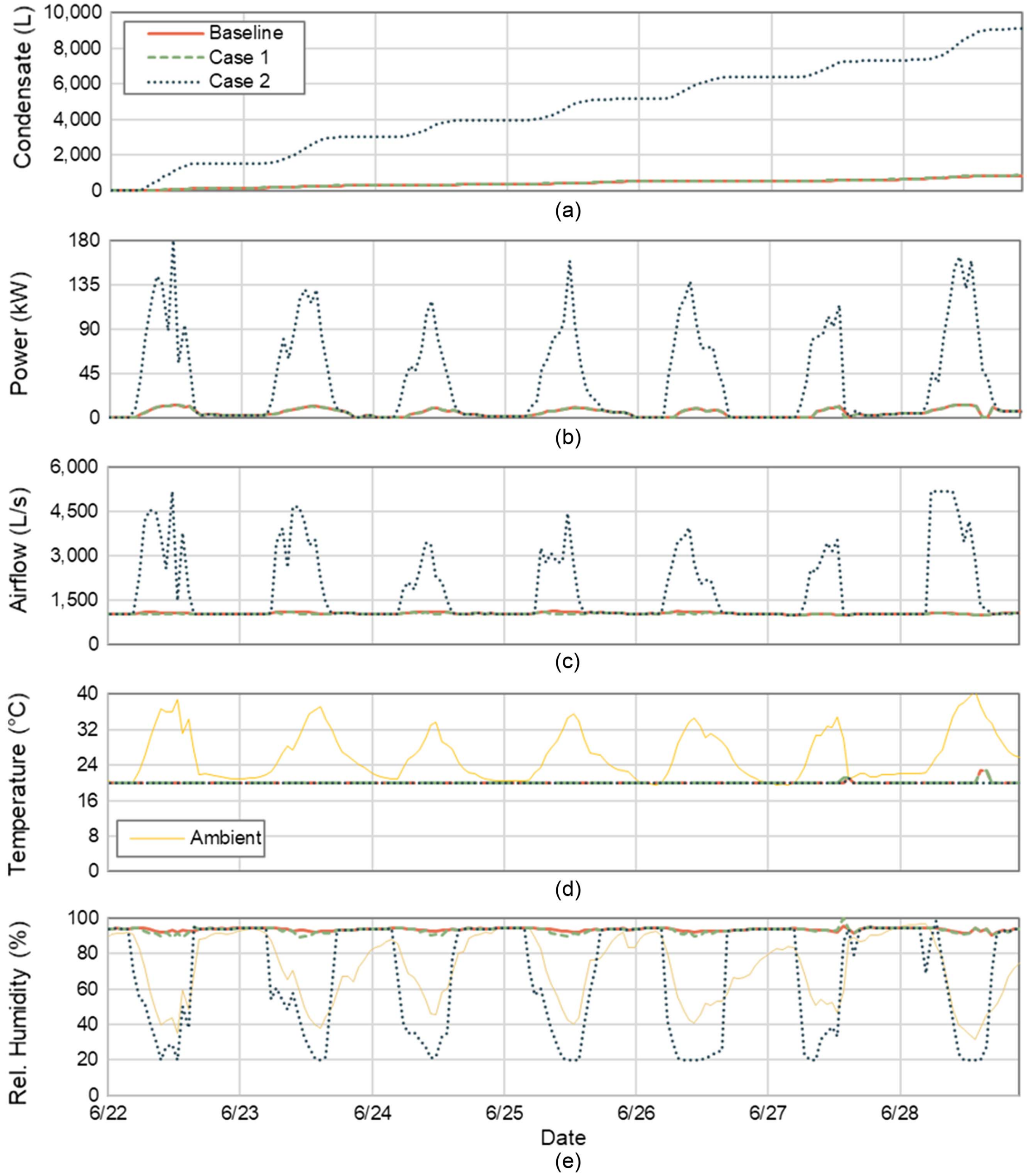

Fig. 7. Comparison of baseline case, Case 1, and Case 2 for (a) condensate collection; (b) power consumption, delivered (c) airflow; (d) temperature; and (e) relative humidity.

Table 2. Summary of case study results

Case	Net positive energy (%)	Condensate (L)	Improvement
Baseline	123	19,082	—
Case 1	123	20,532	+8%
Case 2	50	154,214	+708%

of occupants. Case 2 was reevaluated with a potentially more desirable maximum outside airflow constraint of 1,888 L/s. This evaluation yielded an estimated condensate production of 148,077 L, or approximately only 4% fewer total liters collected than the original Case 2 optimum. Therefore, significant condensate collection may still be achieved under more conservative operating conditions using the method laid out here.

Discussion

The presented case studies demonstrate the immense potential for increasing the amount of condensate produced by a HVAC system through the incorporation of numerical optimization, thereby filling the aforementioned gap in the current literature. Note that these studies had the benefit of both foreknowledge of the energy requirements of the system in the baseline case and operated on the assumption that changes in the HVAC system operation would activate and produce the predicted condensate immediately. To practically apply the presented approach, system operators may need to establish and adhere to daily energy budgets to ensure that the building system-level requirements will not be compromised by the increased condensate production. In addition, if operating decisions are made hourly by building automation systems (BAS), the transient lag is likely to reduce the condensate collection estimated here. However, based on the slow rate of ambient condition change, this reduction is expected to be fairly insignificant, especially in consideration of the magnitude of condensate productivity improvements estimated in the case studies.

The conditions of the overall system must be considered if system-level water consumption benefits are to be realized. Connection to an evaporative cooler may mitigate the condensate production achieved as a result of directing additional cooling to moist air streams for dehumidification. Connection to a dry cooling system is recommended for overcoming this. In addition, operating a HVAC system on a district cooling system may pose challenges to the chilling operation of the AHU by restricting the available water temperature or flow rate. Chilling with a refrigeration system removes this issue while introducing a potentially less efficient cooling system.

As discussed earlier, the presented process, depicted in Fig. 1, may be reproduced without physics-based models. If data are available on the ambient and delivered air conditions, as well as the power consumption and condensate production of the HVAC system, data-driven models may be formed. Using this approach, a large collection of data from the HVAC system over time may be used to fit a metamodel and this metamodel used for optimization in the same manner as the presented case studies. However, care must be taken to avoid extrapolation outside of operating conditions for which data have been gathered. To help here, the building may be intentionally operated toward the edges of its operating parameter ranges, where additional data may be gathered to inform the metamodels.

Conclusions

This work aimed to investigate how a building's HVAC system may be operated to maximize condensate production while upholding user thermal comfort and energy consumption requirements. A physics-based condensate model was presented and validated against data from KBISD, an academic building on Georgia Tech's campus. The sensitivity of KBISD's HVAC system condensate production and power consumption to the system's operational controls and ambient conditions was discussed. Metamodels were developed to quickly represent the physics-based model's estimation of condensate production and power generation. These metamodels were used within an optimization environment to determine how the building's HVAC system may be operated in real time to maximize condensate production while observing thermal comfort and energy constraints. The case studies included here found that the optimized HVAC system operation produced 8% more condensate in an energy preservation strategy and up to 708% more condensate when additional energy was directed toward condensate production. Bolstering condensate production was principally achieved in these studies by increasing delivered airflow, decreasing delivered air relative humidity, and maintaining DAT within thermal comfort constraints. This study contributes to the literature by presenting a practical optimization approach for both substantiating operations to maximize condensate production and for doing so within the energy consumption and thermal comfort constraints active in emerging sustainable building systems.

Future work will aim to apply the operating strategies recommended here within an actual building to validate this operating framework. In addition, efforts will be made to expand the condensate and energy modeling to include more complex HVAC assemblies, such as those that recycle air or use heat recovery devices. Finally, the construction of metamodels alongside actual operating data provides the opportunity for the incorporation of these into model predictive control schemes for optimizing other areas of HVAC system performance in light of real-time operation and current and future constraints. Future work will investigate how actual operating data may be used on a continuous basis to refine metamodels and how these models may be incorporated into BASs to allow for model predictive control of building systems.

Data Availability Statement

The inputs and results of the optimization case studies will be made available alongside this article. The Python-based optimization script that supports the findings of this study is available from the corresponding author upon reasonable request. The actual historical KBISD building level power consumption and production data are proprietary and will not be released.

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Supplemental Materials

Inputs and results are available online in the ASCE Library (www.ascelibrary.org).

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