Behind the Meter: Implementing Distributed Energy Technologies to Balance Energy Load in Virginia

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On my honor as a University student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines.

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Abstract*—One of the principal challenges associated with decarbonization is the temporal variability of renewable energy generation, which is creating the need to better balance load on the grid by shaving peak demand. We analyzed how innovative load-shifting technologies can be used by large institutions like the University of Virginia to shift load and support statewide efforts to decarbonize. To do this, we focused on the University's plans for expansion of the Fontaine Research Park, which is a good model for understanding how these technologies could distribute energy load behind the meter. First, we worked to develop a predictive model to forecast when peak demands will occur and understand how interventions, including heat recovery chillers and thermal storage tanks, might be used to balance load. Then, we extended a statewide energy systems model using the Tools for Energy Modeling Optimization and Analysis (TEMOA) to simulate the ways in which these types of interventions might be scaled to the whole state. Using the energy demand model in conjunction with aggregated institutional energy use data, the team evaluated the effects that broader adoption of distributed energy technologies in Virginia could have on the grid's ability to handle the energy transition. Our study showed implementing distributed energy sources on a state-scale had insignificant effect on balancing load. However, on a microgrid scale, such technologies prove to be a useful resource to decrease peak demand which would allow for further clean energy projects and possible cost reductions.

Keywords—Load Balancing, TEMOA, Distributed Energy Technology (DET), Thermal Energy Storage (TES), Heat Recovery Chillers (HRC)

I. INTRODUCTION (*HEADING 1*)

As of 2020, the University of Virginia (UVA) and the Commonwealth have made commitments to achieve carbon neutrality by 2030 and 2050, respectively. One of the most important unanswered energy challenges is how to reduce peak demand. This concern is of particular importance because energy utilities charge most large institutions based on their peak energy consumption rate from the previous year. This is set to change with utilities transitioning to time-of-use pricing, where energy usage at peak hours incurs greater costs than energy use during off-hours. For this reason, stakeholders at UVA are interested in exploring the potential of load-shifting technologies that would reduce peak energy consumption and save UVA money to finance future sustainable projects.

UVA currently operates a thermal energy storage facility that provides chilled water to the hospital and medical school. A thermal energy storage system is being considered for the development at Fontaine Research Park, a satellite campus that is under development which includes amenities, office spaces, research, academic, and clinical buildings. The thermal storage system is in 'charging' mode as electricity is taken from the grid and used to run chillers that cool the tank's water down to 42°F. The water is stored at this temperature until the hours of peak energy usage when the system changes to 'discharging' mode. In this mode the chilled water is sent out to be used in the buildings for cooling, and is returned to the tank at a temperature of 55°F. The rate of discharge varies based on the season as cooling demand changes with outside temperature; the winter months exhibit a lower demand for cooling than the summer months. Implemented on a state scale, load-shifting technologies like thermal energy storage may accelerate the adoption of time-of-use pricing.

Currently, PJM, the energy grid that Virginia belongs to, sources roughly 13% of its energy from renewable resources [1]. Renewable energy is often less expensive, but its production rates are unpredictable and depend strongly on outside factors such as solar irradiance and cloud coverage. To compensate for renewable resources' dependence on external factors, load-shifting technology will play a pivotal role in adjusting demand to be more conducive to dynamic grid behavior. The first step of this transition, and the focus of this paper, centers around implementing distributed energy technologies (DETs), more specifically heat recovery chillers (HRCs), in conjunction with thermal energy storage (TES).

HRCs greatly increase energy efficiency by saving heat that would otherwise be wasted in the cooling process. HRCs require significant concurrent heating and cooling load. For this reason, and because of the large upfront cost of installation, HRCs work particularly well at large institutions. Universities, military bases, and campuses are uniquely positioned to see a measurable difference in performance due to the large volumes of energy they consume, their centralized infrastructure, and their concurrent heating and cooling loads.

Tools for Energy Model Optimization and Analysis (TEMOA) is an open-source modeling framework for conducting energy systems analysis [2]. TEMOA allows users to create and specify the economic and functional characteristics of energy generating plants and the fuels that they consume. TEMOA also allows users to specify energy demand by time of day, constrain the model with emission caps, and limit the rate of new power plant creation. The model is run for a set time span and can return data from set years over the run's duration. TEMOA has been utilized in previous studies, like one modeling Puerto Rico's energy grid and its change in response to the probability of hurricanes and the implementation of climate mitigation policies [3].

Most other studies involving TEMOA focus on the model's application as a point of comparison for other energy models to verify the tool's accuracy [4] [5]. Such research provides legitimate grounds for modeling the Virginian energy grid in TEMOA to analyze the viability of deploying DETs on a statewide scale.

II. METHODOLOGY

A. *Data Acquisition*

Data used for modeling Fontaine was collected by Facilities Management at the University of Virginia. It is a set of historic electricity (kW) and cooling (kbtu/hr) usage data for proxy buildings[1] at UVA along with corresponding temperatures (F) and relative humidity taken at fifteen-minute time intervals. Corresponding weather data for solar radiation (W/m^2), wind direction (degrees relative to North), and wind speed (m/s) was sourced from the KVACHARL80 weather station located at Scott Stadium. For each building type, average energy usage was determined by dividing each proxy building by its square footage and then averaging all buildings of that type to get the mean energy demand per square foot. In order to avoid data discrepancies, linear interpolation was performed for missing data values. Other predictor variables included whether it was a weekday or weekend, whether courses were in session, and season of the year. The data spans from February 1st, 2019 to June 30th, 2020. To avoid anomalies caused by the COVID-19 pandemic, the time span was reduced down to February 1st, 2019 to March 8th, 2020.

For modeling the state of Virginia, energy use statistics were sourced from The Association for the Advancement of Sustainability in Higher Education's (AASHE's) Sustainability Tracking, Assessment & Rating System (STARS). The STARS database provided recent energy usage statistics from most large universities and colleges across the United States [6]. A summation of total energy use values for Virginian institutions predicted the potential impact that these institutions could have on the overall energy landscape of Virginia should they choose to implement DETs.

B. *Modeling*

Using the statistical software R, linear regression was performed to predict energy demand per square foot using the following predictors: hour of the day, relative humidity, temperature, whether it was a weekday or weekend, season, solar radiation, wind direction, and wind speed. Since the response variable is non-negative, we performed a natural log transformation on the response variable to output positive values, then reconverted the output back to its original form by transforming into exponential form. In order to correct for high correlation in the time series data, we also performed ARIMA modeling on the residuals of the linear model using R's auto.arima() function. The ARIMA output gave a correction factor that was then added to the predictive linear model. Adding the two models together gave an output of average demand per square foot for each building type which was then multiplied by the estimated square footage for each building type.[2] The output of the cooling model was converted from kBtu/hr to kW to be consistent with the units used for electricity demand. In estimating the electricity usage for the cooling demand, an efficiency loss assumption of 25% was applied to account for system losses associated with chillers [7]. The two kW outputs from the cooling and electricity demand were then summed to give an output of overall demand.

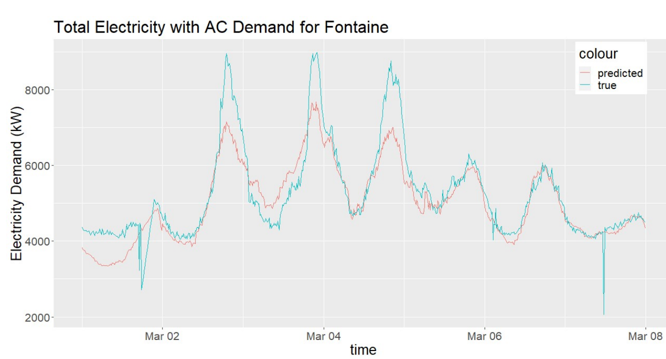

Fig. 1. Linear regression model predicting total electricity and cooling demand for the first week of March 2020 superimposed on the true, observed demand.

[1] The proxy buildings included two academic buildings (Minor Hall, Skipwith Hall), six research buildings (Jesser Hall, Rice Hall, Physical and Life Sciences, Chemical Research Engineering, MR-5, MR-6), and two clinical buildings (Primary Care Center, Battle Building)

[2] 179,000 GSF for academic buildings, 606,000 GSF for clinical buildings, and 500,000 GSF for research buildings.

We modeled the thermal energy storage tank using many of the assumptions outlined from the hospital's system. Figure 2 displays the assumed monthly schedule of discharge rate for the thermal storage tank. We converted discharge flow rates from gal/min to cooling capacity in kW given the parameters of the tank in order to combine kW consumption with electricity consumption. Since we are considering the effect of charging and discharging the thermal storage tank on total electricity consumption in kW, we applied the efficiency loss to the charge and discharge flow rate in kW by dividing by its efficiency factor of 75%, to get kW of electricity used to cool the water. Additionally, the charge rate also took into account efficiency loss from the thermal storage tank itself, assumed to be 5%. Thus, the charge rate was also divided by the TES efficiency factor of 95%.

Month	Discharge Rate (gal/min)
January	500
February	600
March	700
April	800
May	1000
June	1500
July	2250
August	3000
September	2000
October	800
November	700
December	600

Fig. 2. Monthly schedule of thermal energy storage tank discharge rate in gal/min.

We applied the same schedule the hospital uses which discharges between 11:00am to 7:30pm and charges between 8:00pm to 10:30am. Additionally, the transition period between charging and discharging was assumed to be negligible. The outputs of this model were used to qualitatively analyze the technology's behavior on a microgrid scale so it could be applied to institutions across the State using the TEMOA modeling tool.

The TEMOA model used in this project builds off a previously constructed model that simulated energy use in the Commonwealth of Virginia [3] and adds HRCs to the grid. The runs would show the effect of mass implementation of HRCs on hourly distribution of net energy activity (PJ), with a focus during the summer, when the technology's impact would be most significant due to the simultaneous heating and cooling loads.

Three sets of runs were performed to conduct a thorough sensitivity analysis of factors suspected to affect net energy activity. The first set of runs varied the total capacity of HRCs. The second set of runs varied the efficiency of the HRCs at a constant 3,000 MW capacity. The third set did not restrict the building of additional capacity of HRCs and sampled three separate points in time over a thirty-year period: 2025, 2035, and 2045.

Part of TEMOA's output are database files for each scenario. These were transformed using an in-browser converter into a folder of ".csv" files that each represented a table from the database. These files were then read into an R environment and the energy activity of the various power plants were analyzed.

The model aims to explore the relationship between varying input parameters and the degree of load balancing on the grid. It was hypothesized that a larger capacity and greater efficiency would further balance load which is represented by a flatter energy activity curve.

III. ANALYSIS AND RESULTS

Figure 3 shows the intervention of TES to the predicted energy demand for the first week of March 2020. As predicted, the application of thermal energy storage significantly shifted load from the peak grid demand hours that occur in the middle of the day and redistributed demand during the hours of 8:00 pm to 10:30 am. TES in Figure 3 displaced a total of 2,572,500 gallons of chilled water for that week of March.

Predicted energy demand was developed so other institutions could simulate similar load-balancing technologies and thus augment statewide use of TES. Though the predictive model closely resembles real demand trends, there are limitations to the predictive abilities of the tool driven in part that the demand data was collected from only the last year and a half. Due to the COVID-19 pandemic, much of the more recent data cannot be applied given its irregularities. With these data limitations, an analysis using predicted energy demand could not be simulated during the summertime when the benefits of HRCs are most pronounced. Rather, thermal storage intervention was applied to the observed data for the month of July 2019, as seen in Figure 4. TES in Figure 4 displaced a total of 1,181,250 gallons of chilled water from peak hours to off-peak hours for just a single average day in July. Given that cooling demand accounts for 12% of total commercial energy consumption in the US [8], the shift in load dramatically displaced electricity usage as seen in Figure 3 and 4.

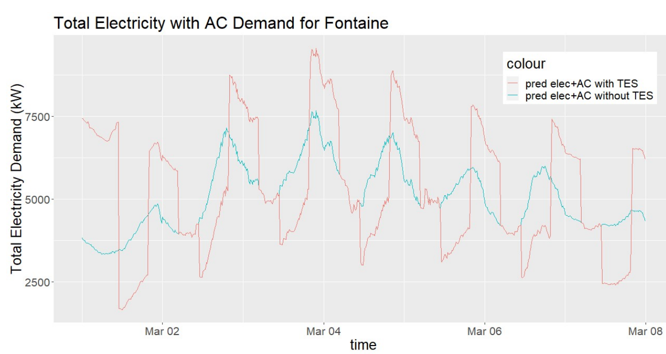

Fig 3. Linear regression model predicting total electricity and cooling demand for the first week of March 2020 with thermal energy storage.

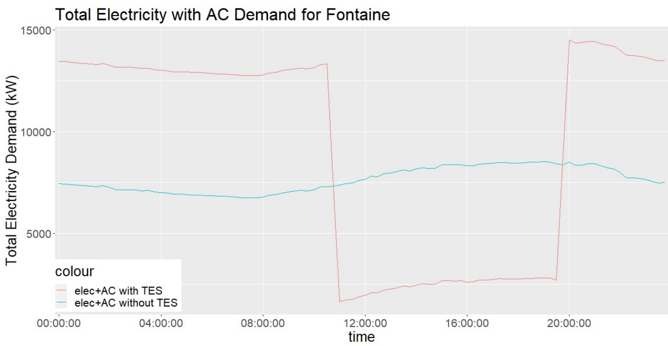

Fig. 4. Total electricity and cooling demand for an average July day based on 2019 historical data with thermal energy storage.

HRCs were then applied to a similar summer day in the TEMOA analysis. The aggregated net energy activity in PJ was graphed by hour over the summer season, both including and excluding HRCs. In addition to the graphical analysis, a multifactor ANOVA test was performed over each set of graphs using a binary HRC inclusion factor and varied each parameter over different runs (efficiency, year, capacity). The ANOVA table examined the difference between the daily and hourly average, a smaller difference indicating a flatter curve overall which implies a more even load distribution.

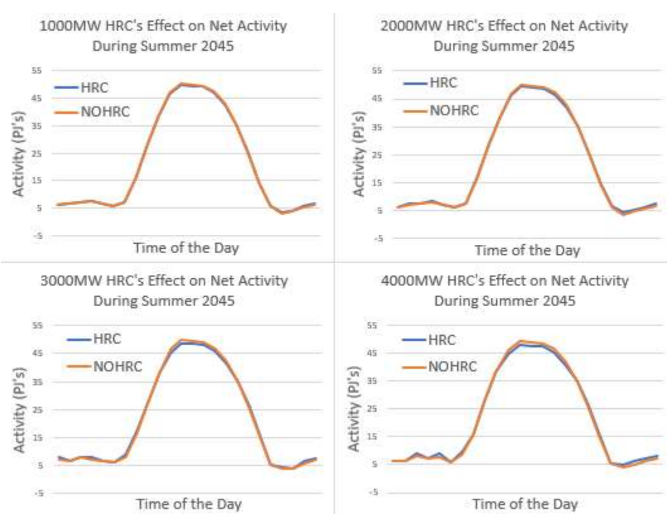

Fig. 5. Projections of HRC implementation at four different capacities 1,000, 2,000, 3,000, and 4,000 MWs.

As shown in Figure 5, varying the capacity between 1,000 and 4,000 MW of HRCs does not have a significant effect on net energy activity. At any of the given capacities, the two output levels nearly overlap, indicating minimal load shifting from the HRCs. This assertion was further supported by the results of a multi-factor ANOVA test, where capacity as an isolated variable had a p-value of 0.965.

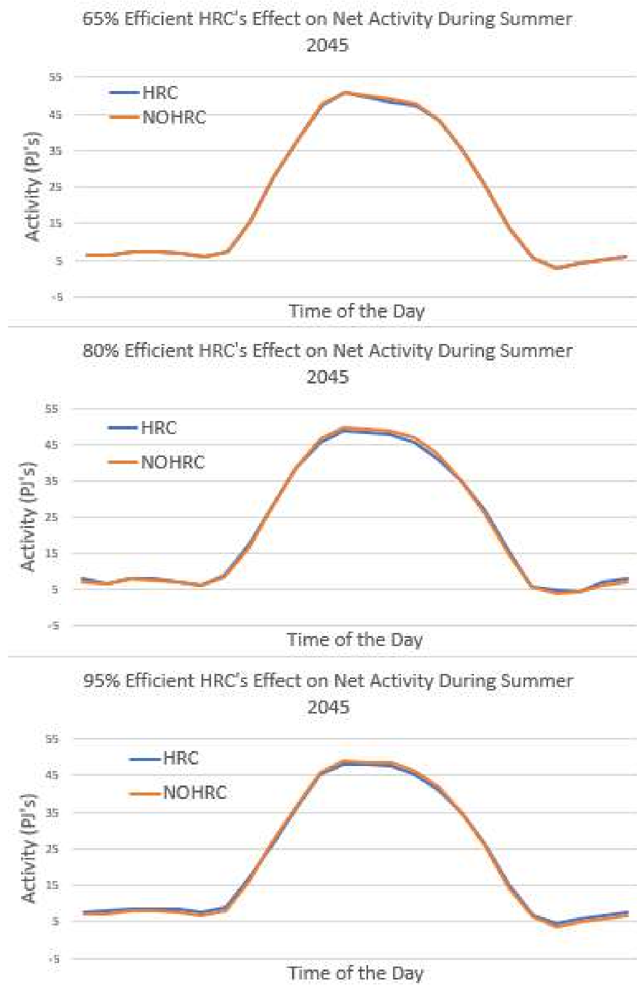

Fig. 6. Changes in efficiency of HRCs between three levels, 65%, 80%, 95%, at a constant 3,000 MW capacity.

Visual inspection of Figure 6 brings about a conclusion that is akin to the previous analysis centered on the effect of capacity manipulation. In the same way, changing efficiency rates for the HRC fails to significantly alter net energy activity, indicating that as a whole, HRCs have a negligible effect on the effectiveness of load-balancing efforts, even with increased efficiency. This assertion is further corroborated by the results of a multi-factor ANOVA test, where efficiency as an isolated variable had a p-value of 0.71.

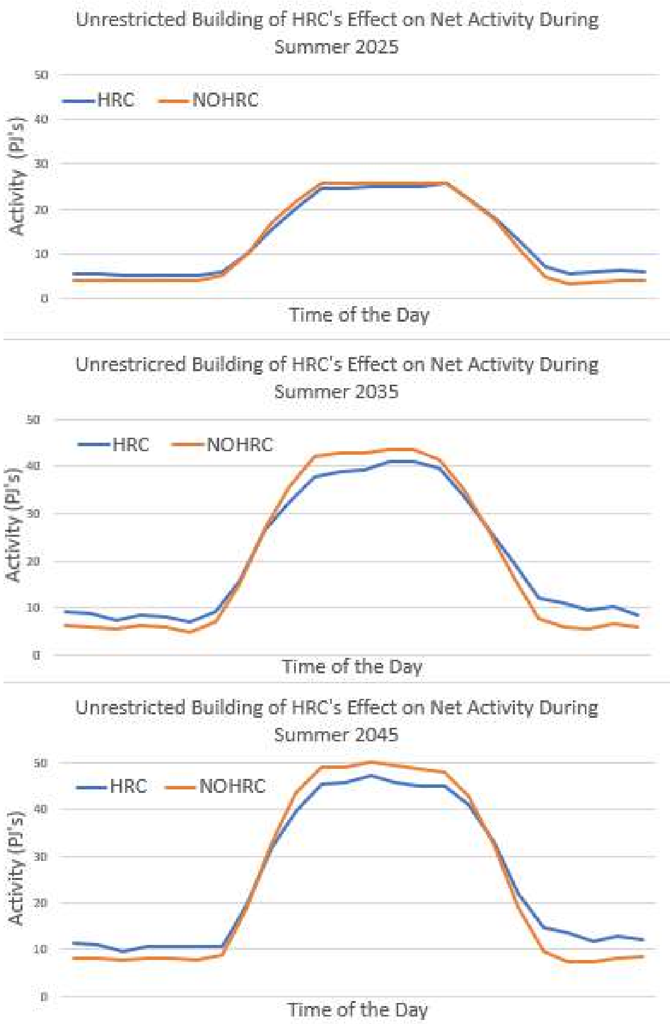

Fig. 7. Unrestricted building of HRCs for 2025, 2035, and 2045 on a statewide basis.

As can be discerned in Figure 7, future grid forecasting indicates the passage of time has a statistically significant effect on the daily energy activity curve. This assertion is further corroborated by the results of a multi-factor ANOVA test, where time as an isolated variable had a p-value of less than 0.01. Note that when the HRC capacity in the model was left unrestricted the capacity grew to 8,400 MW in 2025, 22,600 MW in 2035, and 29,000 MW in 2045.

IV. Conclusion

Currently, we are seeing a national trend toward electrification as the nation transitions away from oil dependent activities. Given the demand implications on the local microgrid, the implementation of TES systems may encourage local utilities to adopt time-of-use pricing. This would further incentivize load shifting activities, in turn supporting future growth of renewables. Such an effect would free up local substation capacities, allowing for more local clean energy projects. However, when scaled to the state level, the findings concluded that mass HRC implementation had no real significant effect on load balancing.

There are some significant considerations when reviewing the results of the model. The largest grid scale battery in the world is currently only 300 MW [9]. When considering that total HRC capacities would need to be in the thousands, this would require massive implementation at nearly all institutions in Virginia. In other words, the amount of capacity needed to become significant is improbable. That being said, HRCs benefit at the institutional level may provide significant cost savings, especially with time-of-use pricing. Further, the resilient nature of such technologies allows institutions to operate more independently from the grid.

Even though the degree of load balancing increases in the future as more technologies are implemented, state resources would be better suited elsewhere. Further research may be conducted to explore other state level technologies to either increase load balancing on a macro scale or increase grid capacities. Potential demand response programs could be implemented to take advantage of the growing number of electric vehicles on the road. Perhaps discounting and paying electric vehicle owners to charge and discharge electricity from the grid may provide more significant results given the growing market. Further, electric bus storage implemented on a state scale may provide similar benefits. Continued research in renewable forms of energy which provide more controlled production would further increase the stability of the grid.

Acknowledgment *(Heading 5)*

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