Coordinated Steam, Power & Emission Economic Dispatch of Multi-energy Campus Microgrids

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***Abstract*—This paper presents a coordinated steam, power & emission economic dispatch (SPEED) model for achieving an economical operation of a university campus multi-energy microgrid. The coordinated scheduling of combined heat and power (CHP) units, as well as high efficiency steam boilers is implemented to optimize the entire campus energy provision consisting of both steam and electricity, while considering the campus emission reduction objective. Impacts of demand charge, load profiles, and practical operating constraints of the campus multi-energy microgrid system are modeled and formulated into the SPEED problem based on recorded campus energy systems' historical operation data. The effectiveness of the proposed SPEED model is demonstrated on a simplified campus multi-energy microgrid system, considering a planned photovoltaic (PV) farm integration and the utility supply. As demonstrated in the simulation results, comparing with the conventional operation solution the university facility is implementing now, the proposed SPEED was capable of coordinating the optimal provision of electricity, steam, as well as emission reduction resulting in overall campus utility monetary savings.**

Keywords—microgrid, economic dispatch (ED), combined heating and power (CHP), photovoltaics (PVs), steam boiler.

NOMENCULTURE

T	Total time intervals
t	Hour index
S	Steam energy output
P	Power energy output
i	Generation source index
$P_{U,t}$	Power utility provision
τ	Power utility purchase price
$P_{PV,t}$	PV farm energy provision
$P_{E,t}$ and $S_{E,t}$,	Excess energy provision
$F_{i,,t}$,	Cost of unit i at t
N_G	Number of onsite DERs
$P_{D,t}$ and $S_{D,t}$	Power and Steam Demand

I. INTRODUCTION

The traditional electricity network, which passively carries energy from a few large power generators to consumers, is evolving to a modernized smart grid, hosting a large number of heterogeneous residential, industrial, and commercial prosumers (such as a campus microgrid), allowing two-way flows of electricity and information. As one of the key smart grid components, microgrids may be connected to the utility power grid, other microgrids, or may function autonomously improving system energy resiliency, reliability, sustainability, and efficiency. While utility-connected, microgrids can optimize their system assets' operation, and thus energy flows, to gain economic benefits through intelligent controls, e.g., transactive control which optimizes operation via cost and power profile signals exchanging [1].

In 2020 alone, the United States experienced a total of 22 unique extreme weather and climate-related disaster events that brought cumulative costs of $95 billion USD [2]. Paired with these extreme weather events are often power blackouts leading to cascading social and economic costs. A growing number of universities including UC San Diego, MIT, Montclair State, Princeton, and Santa Clara University have led the initiative to adopt microgrids or design new incentives in their campus energy systems, providing valuable research for optimized energy provision and improved energy resilience [3]-[7]. Specifically, Montclair State University (MSU) in New Jersey, who enrolls 21,000 students with more than 5,000 living on campus, converted its existing 5.4 MW combined heat and power (CHP) cogeneration, on campus renewables, and onsite boilers to a newly constructed campus microgrid [5]. MSU's campus microgrid is currently employing a centralized SCADA system that includes a load-management system with a built-in model-predictive controller, providing both campus energy resiliency and an estimated economic benefit of $4 million dollars annually. The controller, utilizing the campus's historical demand, adjusts electrical, steam, and chilled water loads and predicts how much energy should be needed from the distributed energy resources (DERs) to improve load shedding and avoid ratchets on electric utility demand charges [8].

Besides, the rapid increase in fuel cost over the past decade has motivated more economic desire to optimize the electricity generation scheduling in microgrids as accurately as possible to meet the real demand [9]-[10]. To allow for a more accurate load following, the time window for intelligent controls of microgrids is constantly shortening, increasing the number of variables to be optimized [1]. Thus, intelligent microgrid controls require complex optimizations to run frequently, further decreasing system run time. This pursuit encouraged extensive research in

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mathematical programming optimization methods to support more frequent generation scheduling over shorter lead times in microgrids [1],[11].

In the modern era, Machine Learning (ML) and Artificial Intelligence (AI) has greatly gained popularity in research to build intelligent microgrid controls via genetic algorithms [12], particle swarm optimization [13], neural networks [14], deep reinforcement learning [15], and especially hybrid techniques to solve the increasingly complex problems. The major drawback in using these methods is that many suffer from specific parameter selection and behave stochastically, resulting in the possibility of providing local minima rather than the definite optimal point of generation.

Growing public awareness of environmental protection urges a revised power dispatch procedure for energy generation systems to account for both cost and emission, such as CO_2 pollutants. The traditional methods of reducing pollution from power stations are limited to plant-level remedies, e.g. smokestack scrubbers, electrostatic precipitators, or by burning lower-sulfur content fuel. Software techniques can also minimize impact on the environment during energy generation while still considering the cost as shown in [16]-[18]. Nash Negotiation was used in [16], Hybrid NSGA II-MOPSO Algorithm was proposed in [17], and Genetic Algorithm-II was implemented in [18], but infinite computation power, local convergence, and difficulty to implement efficiently and effectively in the context of spatial multi-objective problems are all disadvantages of these methods, respectively.

Thus, an efficient and easy to implement microgrid control method requires fast and reliable dispatch algorithms. In this study, a Linear Programming (LP)-based dispatch algorithm is used in providing known convergence properties and high computation efficiency. The proposed LP-based Steam Power & Emission Economic Dispatch (SPEED) is formulated as an extension to conventional Economic Dispatch (ED) models and determines the optimal generation schedules of campus CHP units and high efficiency steam boilers while utility-connected with PV energy supply. As such, the entire campus electrical and steam demands are coordinately provisioned at minimum operating costs under various operating constraints. In addition, the proposed SPEED integrates accurately estimated emission cost into the operating objective to best use the integrated renewable resources and pursue a sustainable multi-energy campus microgrid.

The remainder of this paper is structured as follows: Section II elaborates the modeling of the multi-energy microgrid components, loads, etc. In Section III. the SPEED solution is formulated, and the simulation results are presented in Section IV. Finally, concluding remarks are provided in Section V.

II. System Modeling

In this section, the detailed modeling of a multi-energy campus microgrid's components, and the pricing of different generation resources are presented. The proposed SPEED is performed on a simplified utility-tied campus microgrid neglecting some system operating constraints e.g., DER turn on/off time and ramp rates that are short compared to hourly SPEED intervals [19], and line flow limits which are negligible due to the big capacity margin. The investigated campus multi-energy microgrid contains the following energy supply sources:

- Dispatchable DER source. E.g., 2 CHP cogenerators, 3 steam boilers.
- Utility sources. E.g., electricity, natural gas.
- Non-dispatchable DERs. E.g., a solar PV farm.

Cogenerators use a gas turbine to produce energy in the form of electricity, saving the thermal energy at the bottom part of the cycle to supply steam to centralized facilities. The ramp up rate and efficiency of this cycle is higher than a simple electric utility plant or steam boiler, resulting in an increasingly attractive solution to campus onsite generation. Furthermore, electric utility costs are irregular subject to utility's factors such as: system demand, operating costs, regulations, etc., proving to be more expensive in certain regions and fluctuate with time. The popularity of congenators forces that an efficient campus energy ED model should consider both electricity and steam provision optimization, while coordinating with the utility supply, to cover complete campus economic worth.

A. Dispatchable Units

Dispatchable resources are fueled by the utility and can be scheduled to adjust their energy productions to achieve minimum operating cost. Each dispatchable DER unit has an associated quadratic operating cost curve, showing a changing unit efficiency (power output over fuel cost input). Natural gas (NG) fuel price does not fluctuate significantly in short periods of time (hourly) so a constant fuel price can be considered for daily SPEED operation purpose. The quadratic cost functions of a dispatchable resource could be linearized as in [1] using a piecewise function taking "*q*" points on a cost curve, starting from the minimum generation operating point and ending at the maximum generation operating point. Fig. 1. graphs a linearization example with just two "*q*" points chosen on a cost curve. The linear functions are continuous between the lower and upper bound.

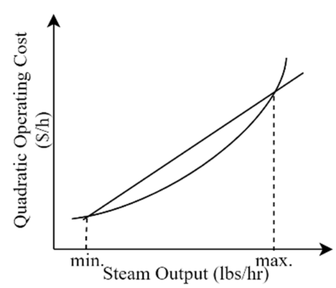

Fig. 1. Quadratic Operating Cost Curve

Each of the campus's 5 dispatchable units (2 CHP, and 3 boilers) are characterized using equations (1) and (2) where efficiency is changing quadratically depending on the unit's dispatch level. A method equivalent to the piecewise function in [1] was used to linearize the cost curves by using their maximum and minimum operation points on the curves and linking them with a continuous linear line, matching the process shown in Fig. 1. Steam and power maximum operation points for each unit are tabulated in Table I. All minimum operation points are set to 0.

$$Efficiency = \frac{Output(Steam)}{Input(NG)} \quad (1)$$

$$Operating\ Cost\ = Output/Efficiency \times Price\ of\ NG \quad (2)$$

TABLE I. CAMPUS UNIT MAX. GENERATION LIMITS

Source	Maximum (MW)	Maximum (lbs/h)
Cogenerator Centaur	3.5	18,000
Cogenerator Saturn	1.2	9,000
Boiler 1	N/A	26,000
Boiler 2	N/A	40,000
Boiler 3	N/A	40,000

The cogenerators use one fuel source to generate steam with electricity as a byproduct, thus having maximum generation limit points for both. Observing historical operation data, the electric energy and steam outputs from the cogenerators are essentially linearly correlated so a ratio was calculated for each cogenerator using equation (3).

$$PowRatio = \frac{lb\ of\ steam}{kWh} \quad (3)$$

Furthermore, a steam to emission ratio was calculated for each NG fired dispatchable unit, using equation (4) and a NG to CO_2 conversion factor provided in [20], $0.12\frac{lb\ of\ CO_2}{cb.ft\ of\ NG}$.

$$EmRatio = (\frac{lb\ of\ CO_2}{cb.ft\ of\ NG})(\frac{cb.ft.of\ NG}{lb.of\ steam}) \quad (4)$$

B. Utility

1) Electricity

The campus's local generation constantly competes with the electric utility to avoid high utility energy cost and demand charges. During periods when the campus has excess energy generation, the microgrid should be constrained to meet at least forecast load and additional power may be net-metered to the electric utility for "profit".

The utility's electricity price estimation was conducted based on the historical campus gross electric load. Historical campus electric load consists of both energy and peak power demands recorded hourly by the campus facility and monthly by the utility. Fig. 2. illustrates the estimated utility's hourly electricity prices for November 16, 2018, a month & day chosen for its average energy and peak demand over the year. Hourly electricity cost was calculated by using the monthly billed total consumption cost from the utility, distributing it evenly to each hour of the month and scaling it across the campus's hourly load curve. The hourly electricity prices depend on various utility charges e.g., distribution and transmission charges, but predominantly on campus load consumption profiles.

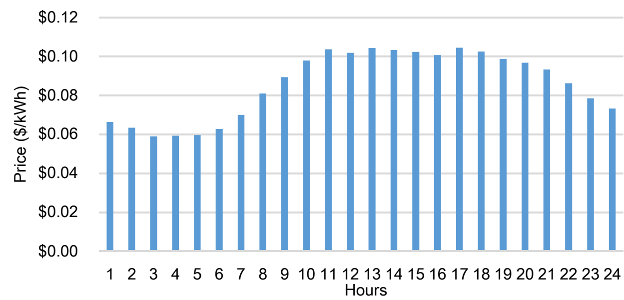

Fig. 2. Hourly Utility Electricity Pricing of November 16, 2018

The electricity provided to the campus's distribution grid is supplied by the PJM Interconnection (PJM) which reported its yearly emissions from June 1, 2018 to May 31, 2019, in [21], disclosing that from its mixed generation, Atlantic City Electric (ACE), the campus's electric energy distributor produces 803.6 $\frac{lbs\ of\ CO_2}{MWh}$.

2) Natural Gas

Natural gas typically has seasonal cost variations, while electricity markets are more volatile having a greater hourly impact on the campus generation units scheduling, forcing them to operate in utility peak hours. Natural gas price was considered to stay constant for each operation day but change monthly due to seasonal price fluctuations. Table IV. in the Appendix lists the campus's monthly NG bill costs in fiscal year 2019. November's gas price, $6.92\frac{\$}{MMBTU}$, was used to calculate the cogeneration and boiler operational cost in the study.

C. Non-Dispatchable PV Farm

Non-dispatchable DERs provide intermittent energy that is not continuously available due to natural factors, e.g., wind and solar irradiation. Helioscope, a web-based sales and design tool for solar professionals was used to integrate a 10.2 MW PV farm into the campus microgrid [22]. Variables from the simulated model as well as solar irradiation data taken from NREL's National Solar Radiation Database were used in equation (5) to determine the hourly PV energy supply. The PV farm does not contain any energy storage devices; therefore, it cannot be dispatched and instead is considered to supply intermittent energy directly to the campus.

$$kWh = Area \times Efficiency \times Solar\ Irradiation \quad (5)$$

D. Campus Load Consumption

1) Electricity Load

Fiscal year 2019's campus electric energy consumption was monitored and recorded as one 15-minute data point each hour. Hourly consumption was calculated by multiplying the 15-minute campus recorded energy consumption by a factor of 4 and scaling by a factor of the utility reported monthly consumption data over the estimated monthly summation. This way, over and under estimation could be accounted for.

2) Steam Load

Unlike the electricity, no hourly campus steam consumption data was recorded, only daily. Therefore, November 16th's steam consumption data was evenly distributed to 24-hours and scaled using [23] university's hourly steam curve. Fig. 3. plots the estimated campus multi-energy microgrid steam and electric demand curves over a 24-hour window on November 16, 2018. We can find that load patterns often do not coincide, as shown in Fig. 3., resulting in periods of excessive supply that is either discharged or sold.

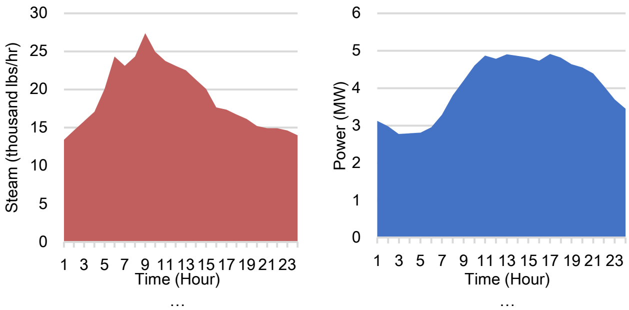

Fig. 3. Hourly Campus Steam (A.) and Electric (B.) Demand

E. Steam and Electricity Oversupply

Campus facilities are guaranteed that electric utilities will purchase their excess electricity at a price based on the utilities "avoided cost" [24]. Avoided cost is the cost that the utility would incur if it provided the electricity itself, at the time. A conservative average avoided cost, \$0.05/kWh, was considered to stay constant and the power exported, P_E, from the microgrid to the utility grid varied based on the hourly optimal SPEED solution. Equation (6) is used to calculate the profit from selling electricity back to the utility grid.

Steam on the other hand, quickly loses its thermal energy and its current distribution systems only circulate the campus, disallowing excess thermal energy to supply off campus facilities. Excess steam may be produced but it is discharged into the environment at the unit's expense.

$$F_{E,t}(P_{E,t}) = P_{E,t} \times (\$0.05) \tag{6}$$

III. SPEED FORMULATION

In this section, the SPEED model is proposed and formulated as a LP problem. The objective of the SPEED is to minimize the total campus energy provision cost over T periods (hours) as shown in (7), considering the NG fuel cost to operate each dispatchable cogenerator and boiler ($F_{i,t}$), total emission cost of the dispatchable DERs and electric utility (FE_t), the electricity purchase cost from utility grid ($FU_{U,t}$), and the profit ($F_{E,t}$) from excess electricity sold back to utility grid at \$0.05/kWh, all the while complying with the multi-energy microgrid system components' physical constraints (10)-(11), and the campus energy balances (8)-(9) for both steam and electricity. Certain constraints on the DER resources such as losses and ramp rates are not implemented for simplification, although they exist in a real system. The operating cost of each dispatchable DER unit was modeled using their average efficiency and NG price with equations (1) and (2).

$$\sum_{t=1}^{T}\sum_{i=1}^{N_G} \left(F_{i,t}(S_{i,t}) + FE_t\left(\sum_{i=1}^{N_G} E_{i,t} + E_{U,t}\right) - F_{E,t}(P_{E,t}) + FU_{U,t}(P_{U,t})\right. \tag{7}$$

To incorporate the solution's carbon dioxide (CO_2) environmental impact into the SPEED model, emissions are considered as an additional cost. Emission cost was based on a measure in dollars of the long-term damage done by a ton of CO_2 emissions in a given year [25]. 2020's 3% average CO_2 emission costs from [25] was used, tabulated in Table II. with their unit emission ratio.

Energy Balance

The electricity and steam demands.

$$\sum_{i=1}^{N_G} P_{i,t} + P_{U,t} = P_{D.t} + P_{E,t} - P_{PV,t}, \qquad t = 1,2,\ldots\ldots,T \tag{8}$$

$$\sum_{i=1}^{N_G} S_{i,t} = S_{D.t} + S_{E,t}\,, \qquad t = 1,2,\ldots\ldots,T \tag{9}$$

Unit Opertaing Constraints

The generation capacity limits of dispatchable DERs provide a set of inequality constraints expressed as

$$P_{i,min} \le P_{i,t} \le P_{i,max} \qquad \forall(i,t) \tag{10}$$

$$S_{i,min} \le S_{i,t} \le S_{i,max} \qquad \forall(i,t) \tag{11}$$

where $P_{i,max}$, $S_{i,max}$ and $P_{i,min}$, $S_{i,min}$ are the maximum and minimum generation capacities of resource *i*, respectively.

Emisssions

Emissions ($\frac{lb\ of\ CO_2}{h}$) from on campus DERs depend on the steam provision and their corresponding emission rates

$$E_{i,t} = EmRatio \times S_{i,t} \qquad \forall(i,t) \tag{12}$$

and the emissions from utility energy provision are calculated using ACE's current emission rate of 803.6 $\frac{lbs\ of\ CO2}{MWh}$.

Cogenerator Power Output

A cogenerator's power provision is dependent on its steam provision.

$$P_{i,t} = PowRatio\ \times S_{i,t} \qquad \forall(i,t) \tag{13}$$

IV. SIMULATION RESULTS

The performance of the proposed SPEED was demonstrated on the multi-energy campus utility plant illustrated in the energy flow diagram, Fig. 4.

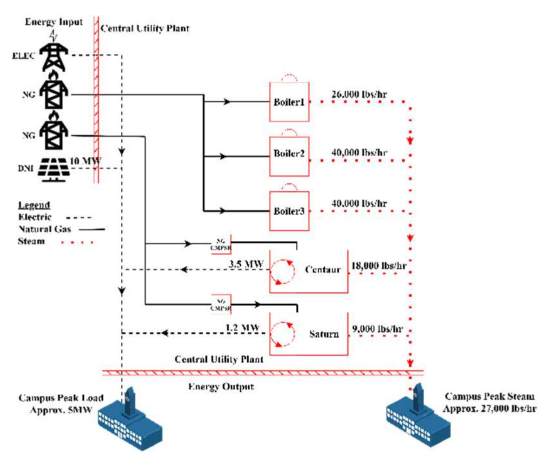

Fig. 4. CUP Energy Flow Diagram

The modeled DERs, utilities, and loads presented in Section 2 are used in the SPEED model to compare the benefits of the proposed SPEED solution over the campus's conventional operation. The SPEED model optimizes one day's DER units operation for T= 24 (hours). The multi-energy microgrid SPEED model was executed in 0.001 seconds on an Intel Core i7 1.5 GHz with 16GB RAM. Note that the calculated savings are based on historical data, therefore, savings may not align with actual numbers at the time of use.

The energy outputs, $P_{i,t}$ and $S_{i,t}$ from each DERs in each hour (t) over the 24-hour time period were optimized to minimize the total energy and emission costs. Table II denotes all the input information calculated with models in Section II and used in the simulation. Tabulated are each source's emission price, DER efficiency, emission rate (*EmRatio),* and power ratio of each cogenerator (*PowRatio*).

TABLE II. SIMULATION VARIABLES

Source	Emission price $(\frac{\$}{lb\ of\ CO2})$	DER Efficiency $(\frac{lb.of\ steam}{cb.ft.of\ NG})$	Power Ratio $(\frac{kWh}{lb.of\ steam})$	Emission Ratio $(\frac{lb.of\ CO2}{lb.of\ steam})$
Boiler 1	0.019	0.7354	0.00	0.1631
Boiler 2	0.019	0.8984	0.00	0.1335
Boiler 3	0.019	0.8538	0.00	0.1405
Centaur	0.019	0.4164	0.1767	0.2881
Saturn	0.019	0.4752	0.1298	0.2524
ACE	0.019	0.00	0.00	0.8036 $(\frac{lb.of\ CO2}{kWh})$
PV	0.00	0.00	0.00	0.00

Operating Boiler 2 and cogenerator Saturn amounted to the least amount of fuel cost. However, as seen in Table II., cogenerator Centaur is more efficient in producing more electric power with the same amount of steam production, making it the favorable generator.

The PV farm was assumed to have no operating cost or emission cost considering the short total time interval. The simulated PV farm energy output changed with respect to the area (40 acres) and direct normal irradiance (DNI), graphed in Fig. 5. Data from NREL's National Solar Radiation Database, for hourly DNI on November 16, 2018, the day under study, was used in the simulation.

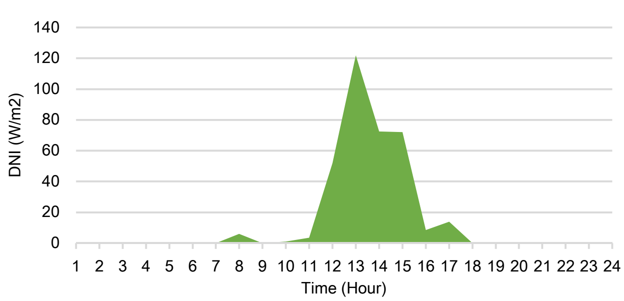

Fig. 5. Solar Irradiation for November 16, 2018, Lat.36.69 N Long.75.42 W

A. *Campus 24-hour SPEED Results*

The simulation results of the proposed SPEED model for steam and electricity generation outputs are shown in Figs. 6-7, respectively. It is observed that a majority of the savings occur at the hours 12~15 due to the utility electricity price spikes, high PV production, as well as high campus steam demand. Total campus energy system cost optimized by SPEED was \$10,912.99.

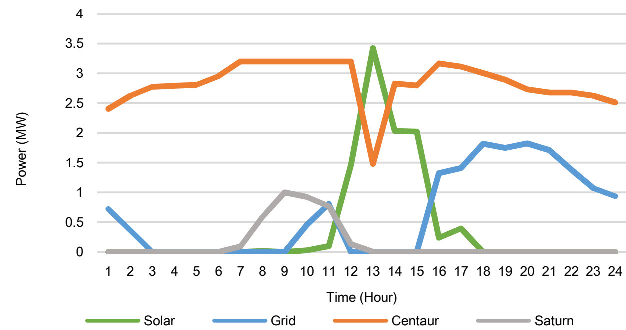

Fig. 6 Hourly generation power curves

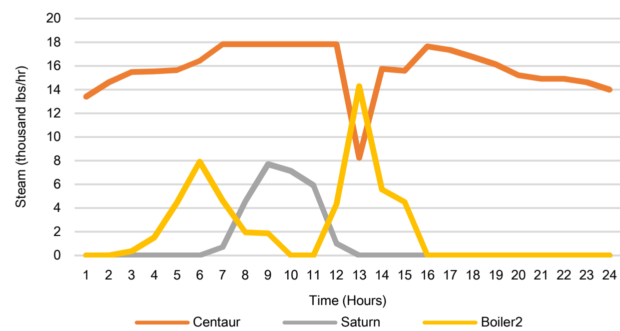

Fig. 7 Hourly generation steam curve

B. *Comaprison with Conventional Solution Result*

For a fair comparison, the currently operating medium/low voltage campus electricity grid and steam distribution system with the planned PV farm was considered to simulate the conventional solution implemented by the campus facility. November 16th's historical data was used to calculate the conventional campus energy system operating and emission cost. Cogenerator Saturn was scheduled at a constant provision to meet the campus steam load demand, with electricity as a byproduct, while two high efficiency boilers, Boiler 2 and 3, were scheduled to cover peak steam demand. Similar to the boilers, the utility grid covered remaining electricity demand after cogenerator and PV supply. Excess electricity was sold back to the utility grid at \$0.05.

Table III. compares the costs of the two operating solutions, conventional vs. SPEED, to meet the hourly multi-energy load demands. The total generation and emission cost optimized by SPEED was \$10,912.99 vs. \$12,865.73, the total retrospective operation cost. The SPEED model contributes to a 18.95% saving in energy cost and a 0.18% increase in emissions compared to the conventional operation. The PJM system mix relies on a variety of energy sources, with majority being gas (39%) and nuclear (35%), which makes it a challenge for onsite generation to compete with the utility grid emission efficiency until more renewables are integrated. Although energy prices vary seasonally and on a day-to-day basis, based on the one-day's simulation results, a $710,192.96 yearly total cost saving could be estimated.

TABLE III. COST COMPARISON

	Emission Cost	Fuel Cost	Electricity Purchase	Total Cost
Retrospective	$2,568.79	$4,753.06	$5,536.91	$12,858.73
SPEED	$2,573.40	$6,892.33	$1,447.26	$10,912.99

V. CONCLUSION

In this paper, the authors proposed and successfully implemented a new campus microgrid energy management approach, SPEED, via optimal scheduling of campus dispatchable DERs. Multiple energy demands (steam and electricity) which are naturally coupled, are coordinately provisioned via the proposed SPEED solution. Simulation results using practical historical data recorded by the campus facility and the utilities demonstrated its efficiency in achieving a big monetary saving for the entire campus over the conventional operation solution employed by the university facility. In addition, LP-based problem formulation provides a stable convergence and quick computation efficiency.

APPENDIX

TABLE IV. ROWAN UNIVERRSITY'S BILLED FY19 NG PRICES

Month	$/MMBTU
Jul-18	$9.86
Aug-18	$5.41
Sep-18	$23.67
Oct-18	$6.48
Nov-18	$6.92
Dec-18	$7.03
Jan-19	$5.80
Feb-19	$5.36
Mar-19	$5.05
Apr-19	$5.21
May-19	$5.76
June-19	$4.82

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