HYBRID SOLAR CHP MICROGRID OPTIMIZATION: PYTHON CODE FRAMEWORK USING REAL EQUIPMENT DATA

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Abstract:
This paper presents a dynamic optimization methodology, developed in Python, for hybrid microgrid systems that combine Photovoltaic (PV) generation with Combined Heat and Power (CHP) engines. The proposed method, in contrast to traditional models that depend on theoretical assumptions or fixed software platforms, directly integrates manufacturer-specific data for chillers and CHP engines, thus improving precision in equipment sizing and operational planning. The methodology is supported by case studies conducted in three cities: In August, Alexandria's maximum cooling load was 935.5 kW with 184.5 kW of excess power, while Kuwait's cooling demand was higher at 2810.1 kW with 168.6 kW of excess energy. In January, however, 3360 kW were required to meet Calgary's heating needs. These results demonstrate how the framework can improve system performance in a range of regional and seasonal settings. By combining real-time climate modelling with actual manufacturer data, the study fills a clear gap in the literature. It offers a more practical substitute for multi-software optimization techniques. The model's precision and pertinence are validated through comparison with industry catalogues. The framework is advised for evaluation using other manufacturers' datasets and should be expanded to incorporate thermal storage, demand-side management, and battery systems.

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1. INTRODUCTION

For sustainable energy management, CCHP systems are crucial, particularly for microgrid design and operation. By producing heat, cooling, and electricity, these systems offer a cohesive strategy for increasing energy efficiency. However, developing systems that can effectively integrate renewable energy sources, adjust to shifting weather patterns, and balance power supply and demand remains a challenge. This research presents a new approach to CCHP microgrid optimization based on the creation of a specialized software application that integrates dynamic load estimates based on variable user inputs. The code enables accurate cooling and heating load calculations by considering important factors such as building characteristics, relative humidity, outdoor temperature, and renewable energy potential. The model presented in the research dynamically aligns electricity production from renewable sources with actual energy consumption using real-world equipment data, from motors to chillers, unlike traditional methods that rely on static assumptions. This method combines theoretical modelling with practical application to guarantee that the outcomes are both academically sound and easily applicable to engineering scenarios. This research is unique because of its thorough methodology, which combines renewable energy analysis with real-time load balancing for real equipment. The simulation enables a

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comprehensive evaluation of engine and chiller performance under various operating conditions by utilizing real manufacturer data. By using information from industry catalogues, the method ensures that the results are relevant for academic research and based on real-world engineering applications. This research advances the design and optimization of hybrid CCHP microgrid systems by providing a tool that combines academic rigor with practical application. The research also addresses the challenges of power system optimization through load distribution, seasonal energy assessment, and careful equipment selection.

2. LITERATURE REVIEW

Recent studies on CCHP microgrids have predominantly concentrated on optimization frameworks; however, most of the research neglects the practical incorporation of actual equipment data and dynamic environmental variables. Ukaegbu et al. [1] formulated a solar-assisted CCHP optimization model utilizing the Harris Hawks Optimization (HHO) method to ascertain Pareto-optimal solutions, hence improving exergy efficiency and mitigating CO_2 emissions. They also proposed hybrid neural methods for improving convergence. While effective, the study remains computational, lacking application to catalogue-based systems. Similarly, Abbas [2] highlighted that renewable-integrated CCHP microgrids can achieve efficiencies exceeding 80% and reduce costs, with penetration rates surpassing 150%, but did not present a load-based optimization methodology. Ye et al. [3] introduced a bidirectional hydrogen-CHP system that utilizes a multi-objective evolutionary algorithm to optimize carbon, cost, and efficiency, incorporating hydrogen energy storage. However, they faced issues related to complexity, investment risk, and operational cost.

Additional studies have further emphasized the importance of system-level control and management. Luo et al. [4] presented a two-phase CCHP control model, featuring predictive and real-time adjustments, for handling renewable variability. Marino et al. [5] demonstrated the coordination of building-cluster microgrids using demand forecasts and risk-aware dispatch, while Yang et al. [6] applied cooperative game theory to allocate energy and costs among microgrids, thereby enhancing decentralized resilience. Yuan et al. [7] proposed a comprehensive evaluation framework for CCHP, incorporating economic, reliability, and environmental metrics. Zhao et al. [8] investigated the role of electrical energy storage in stabilizing CCHP output, particularly under variable renewable energy generation, thereby validating its cost-effectiveness. Furthermore, Smaisim et al. [9] integrated wind, PV, and batteries in a CHP microgrid using a load-optimized control algorithm. Olympio et al. [10] compared centralized versus decentralized CHP systems in terms of cost and emissions, concluding that distributed architectures become more viable as renewable penetration rises.

3. RESEARCH GAP AND NOVELTY

Despite these contributions, significant gaps persist in bridging simulation models with practical engineering applicability. Specifically, most prior works do not utilize real-world equipment catalogues for chillers and CHP units, fail to compute monthly thermal loads based on actual climate data, and seldom model cooling-electric energy coordination using validated design methods, such as those outlined in the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE). Furthermore, surplus power, particularly thermal, has been treated simplistically without properly distinguishing between usable thermal energy, dumped heat, and grid-exportable electricity. This study introduces a Python-based simulation tool that fills these critical gaps. It integrates real manufacturer data from Carrier chillers and Viessmann CHP units, performs monthly load computations based on building design and environmental data, and automatically selects and sizes equipment to match cooling and electrical demands. The system dynamically balances generation and load across seasons and climates, supports categorization of surplus power (electrical vs. thermal), and enables the scalable, cost-efficient design of hybrid PV-CHP microgrids (Figs. 1 and 2). Thus, the novelty lies in offering a transparent and extensible platform that combines catalogue-based engineering design with climate-driven energy modelling, making it suitable for researchers, system integrators, and policy planners.

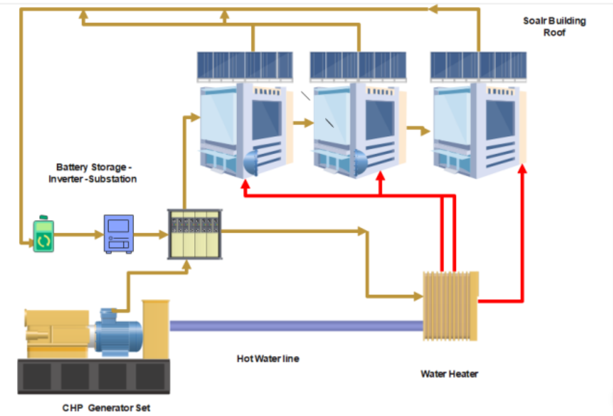

Fig. 1. Microgrid for heating utilizing combined heat and power with solar integration on the rooftop

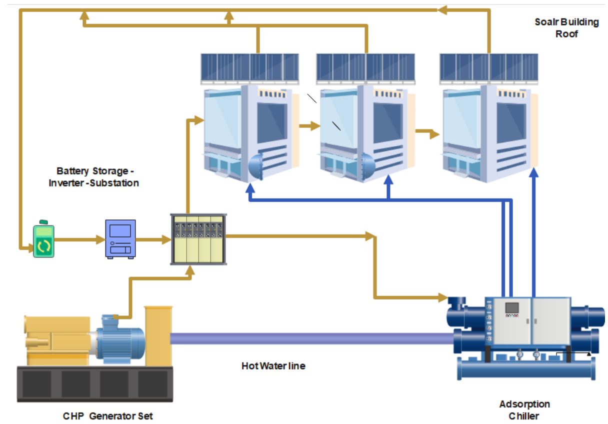

Fig. 2. Integrated heat and power solar systems on a rooftop microgrid for cooling applications

4. MATERIAL AND METHODS

4.1 Climatic and Radiation Data

The PV potential across various global locations was assessed using solar radiation data from the National Solar Radiation Database (NSRDB) provided by the U.S. National Renewable Energy Laboratory (NREL) [11,12]. Energy generation for a standardized 4 kW DC system, assuming standard test conditions (STC), was estimated using the PVWatts calculator. This corresponds to an approximate panel area of 25 m². High solar insolation areas, such as Alexandria, Kuwait, and Mumbai, produce roughly 6,954 kWh, 6,387 kWh, and 6,281 kWh annually, respectively, according to the analysis. On the other hand, temperate regions like Calgary and London produce much lower annual outputs, 5,006 kWh and 3,555 kWh, respectively, due to lower solar irradiance.

Monthly trends in solar radiation further support this discrepancy. London records as low as 0.68 to 1.86 kWh/m²/day in winter months such as December and January, while Alexandria and Kuwait consistently receive between 6.1 and 7.8 kWh/m²/day during the peak months of April to August. With yearly averages of about 4.3 and 4.46 kWh/m²/day, respectively, Calgary and New York exhibit moderate solar availability. The comparative study emphasizes how solar resource variability significantly affects PV performance. It guides the thoughtful installation of PV-integrated microgrids, especially in areas with a lot of solar energy.

4.2 Cooling Load Calculations

The present study utilizes a Python-based computational tool to assess monthly cooling loads for buildings, considering climatic conditions and building envelope characteristics. This approach integrates monthly meteorological inputs, namely, external temperature and relative humidity, from established weather datasets [13]. The code first converts all inputs into British thermal units (BTU) for intermediate calculations, then reverts to SI units for output. Sensible heat gain, primarily caused by temperature variations across the air handling unit and wall transmission loads, is calculated using the cooling load temperature difference (CLTD) methodology and the wall's surface area and thermal transmittance (U-value) to evaluate monthly cooling demand. Remarkably, when relative humidity exceeds 50%, the model dynamically incorporates latent heat gain to account for the additional energy required for dehumidification. This component ensures that both dry-bulb temperature and moisture content are considered when estimating cooling energy requirements. Sensible, latent, and combined totals are used to separate the overall cooling load, which includes ventilation and air infiltration effects. A thorough grasp of how climate variability impacts building thermal demands throughout the year is made possible by the monthly plotting of the results. The proper sizing of systems and efficiency analysis are guided by the detailed insights into seasonal cooling behaviours that this thermodynamic segmentation offers.

4.3 PV Energy Estimation

The PV module performance is evaluated using solar radiation data sourced from the National Renewable Energy Laboratory (NREL) via the PVWatts calculator [11,12]. In Alexandria, for instance, a PV array spanning 850 m² yields an estimated 2,897 kWh of daily energy output during January, assuming an average daily solar irradiance of 4. kWh/m² and a system efficiency of 85%. To accommodate system inefficiencies and ensure uninterrupted service, the battery storage capacity is oversized by 20%, yielding a required daily storage capacity of approximately 3,476 kWh. This setup provides an average continuous power supply of 120 kW for 24 hours. Significant heterogeneity in solar potential is revealed by cross-regional research. Cities like Alexandria, Kuwait, and Mumbai see elevated irradiation levels, leading to increased photovoltaic energy production and reduced relative battery storage needs. Conversely, cities such as London and Calgary demonstrate diminished irradiance levels, especially during winter, leading to proportionately lower daily energy outputs and an increased dependence on energy storage. These results highlight how important local climate is when evaluating the feasibility and effectiveness of PV-based microgrids.

4.4 Combined Heat and Power (CHP) Performance

The combined heat and power (CHP) component is modelled using technical specifications from Viessmann's Vitobloc product line, which includes natural gas-powered units with high electrical and thermal output efficiencies [14]. These CHP units are designed for continuous operation in facilities with simultaneous heat and electricity demands, thereby maximizing fuel utilization. For example, the Vitobloc NG 15 delivers 15 kW of electrical output and 38.3 kW of thermal energy, achieving an overall system efficiency of 100% through full heat recovery. Larger units, such as the Vitobloc Em-100/173, generate 99 kW electrically and 173 kW thermally, with an efficiency exceeding 93%. The Em-530/660 model delivers 530 kW of electric power and 688 kW of thermal power, achieving over 90% efficiency. These real-world performance metrics enable precise selection and sizing of CHP systems according to calculated building loads. By integrating catalogue-based manufacturer data into the simulation framework, the model ensures practical applicability and accurate alignment with operational parameters. This methodology not only enhances the credibility of the model outputs but also facilitates direct translation into real-world hybrid energy systems, where PV generation supports electrical loads and CHP units provide both backup power and heating/cooling integration.

4.5 Absorption Chiller Integration

The absorption chiller, as in Fig. 3, used in this study is the carrier 16JL/JLR lithium bromide (LiBr)-water system, which provides a Fig. 2 integrated heat and power solar systems on rooftop microgrid for cooling applications, thermally activated cooling solution using hot water as its driving energy source [15]. This system is widely recognized for its energy efficiency and suitability for commercial and industrial applications where waste heat or combined heat and power (CHP) sources are available.

Operating with a lithium bromide solution, the chiller relies on the endothermic evaporation of water under vacuum conditions to deliver cooling. The hot water used to regenerate the LiBr solution typically exhibits a temperature differential of 10–15°C across the generator. The chiller is designed with an integrated control mechanism that dynamically adjusts the solution concentration to avoid crystallization, one of the primary operational risks in LiBr systems. This allows the system to maintain high reliability and long-term performance.

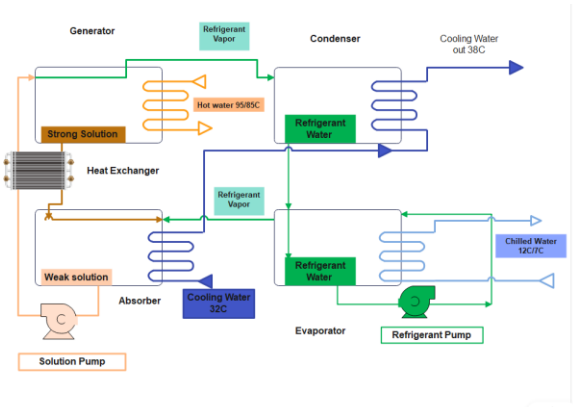

Fig. 3. Schematic of an absorption chiller

Carrier's product line includes multiple models within the 16JL/JLR family, offering cooling capacities ranging from 264 kW to over 2,100 kW, with corresponding hot water flow rates from approximately 23 to 257 m³/h, depending on the model. The coefficient of performance (COP) values range between 0.65 and 0.72, reflecting variations in operating temperature conditions and the use of different hot water temperature levels (typically either 80°C for "b" models or 90°C for "a" models). The system maintains a low auxiliary pump power requirement, usually not exceeding 3.7 kW, which further enhances its operational efficiency.

For example, the 16JL-052A model efficiently uses the thermal energy that is available by delivering a cooling capacity of 2,135 kW with an input heat requirement of 2,988 kW and a coefficient of performance (COP) of 0.71. Such specifications allow the absorption chiller to seamlessly integrate into CHP systems by utilizing recovered heat from gas engines or other thermal sources to displace conventional electrically driven chillers.

This integration is crucial in hybrid microgrid applications where both PV and CHP systems are deployed. By leveraging waste heat from CHP engines, the carrier absorption chiller effectively reduces the need for electrical cooling, thereby increasing the overall system efficiency and contributing to operational cost savings and reduced environmental impact.

4.6 Model and Methods

A dynamic algorithm for optimizing hybrid microgrid systems that combine PV solar power and CHP engines is presented in this work. The model uniquely employs actual manufacturer data for both absorption chillers and gas engines to deliver accurate, site-specific results. It is designed to determine the optimal configurations of solar arrays, chillers, and CHP units that satisfy cooling, heating, and electrical demands under varying climatic conditions.

The model operates monthly, incorporating real meteorological data and solar irradiance to evaluate its performance throughout the year. Building-specific inputs such as geometry, wall type, air change rates, and appliance loads are processed to compute cooling and heating demands, considering both sensible and latent heat loads. The outputs of the code are visualized in graphs and text summaries that show energy consumption, PV generation, and optimal equipment selection. This framework allows for highly adaptive and efficient microgrid design, tailored to fluctuating seasonal conditions and regional requirements. The Model algorithm is defined in Figs. 4 and 5.

PV power is calculated as a function of roof area, utilization ratio, and solar radiation for each month. When PV output is insufficient, the algorithm selects appropriate CHP engines to meet the residual load. The engine selection algorithm ensures that both electrical and thermal demands are fulfilled without oversizing, based on catalogue performance data. Excess generation is also tracked and analysed to inform storage or export strategies.

Chiller selection is based on a hierarchical algorithm. Monthly cooling demand is matched to chiller models beginning with the most minor units and scaling up until the full demand is met. If the required capacity exceeds the largest available unit, multiple chillers are selected. This stepwise matching ensures minimal energy waste while maintaining performance.

Code Algorithim

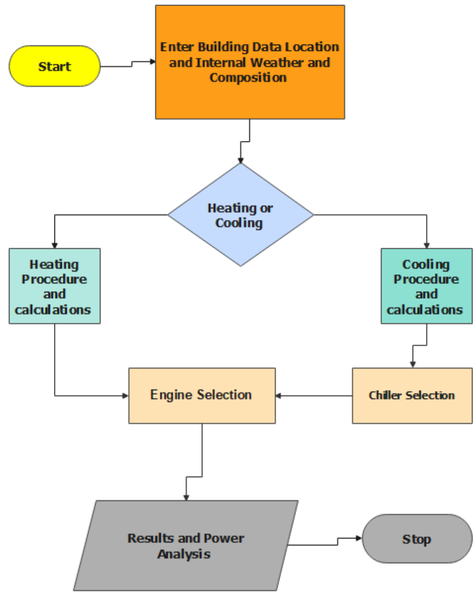

Fig. 4. The algorithmic coding procedure for inputs, outputs, and computational sequence

Similarly, engine selection prioritizes exact matching of monthly energy deficits, accounting for both electrical output (engine) and thermal energy (thermal). For high-load periods, large engines such as the EM-530/660 are used. For lower deficits, smaller engines are selected, always ensuring operational efficiency across the year. CHP engines serve dual roles by covering electrical demand and providing the thermal input required for chiller operation. Chillers are primarily driven by thermal energy, but a small amount of electricity may also be used for pumping and controls. The following equations form the core energy balance logic for matching generation with demand, and evaluating any excess:

$$\boldsymbol{P}_{PV} + \boldsymbol{P}_{\text{engine}} + \boldsymbol{Q}_{\text{thermal}} \geq \boldsymbol{Q}_{\text{chiller}} + \text{electric load} \quad (1)$$

This equation ensures that the combined energy supply - consisting of PV electricity ($\boldsymbol{P}_{PV}$), engine electricity ($\boldsymbol{P}_{\text{engine}}$), and thermal output ($\boldsymbol{Q}_{\text{thermal}}$) fully satisfies the total monthly building energy demands. The right-hand side accounts for cooling loads handled by absorption chillers ($\boldsymbol{Q}_{\text{chiller}}$), which are driven by $\boldsymbol{Q}_{\text{thermal}}$, and all electrical loads (lighting, appliances, auxiliary systems). This equation is essential in determining the required engine capacity each month.

$$\mathit{Residual\ energy\ balance} = \boldsymbol{P}_{\boldsymbol{PV}} + \boldsymbol{P}_{\text{engine}} + \boldsymbol{Q}_{\text{thermal}} - \boldsymbol{Q}_{\text{chiller}} - \mathit{electric\ load} \quad (2)$$

This expression calculates the net energy surplus or deficit after meeting all monthly cooling and electric demands. A positive result indicates that there is excess energy available for storage, grid export, or buffering inefficiencies. A negative result suggests undersupply, which might call for demand management or more engine capacity.

With little waste and no unmet loads, this methodical approach guarantees that energy generation and demand are balanced. This research is novel because it uses fine-grained monthly simulation, dynamic load matching across thermal and electrical subsystems, and real catalogue data. When combined, these characteristics improve hybrid PV-CHP microgrid systems' accuracy, adaptability, and practicality.

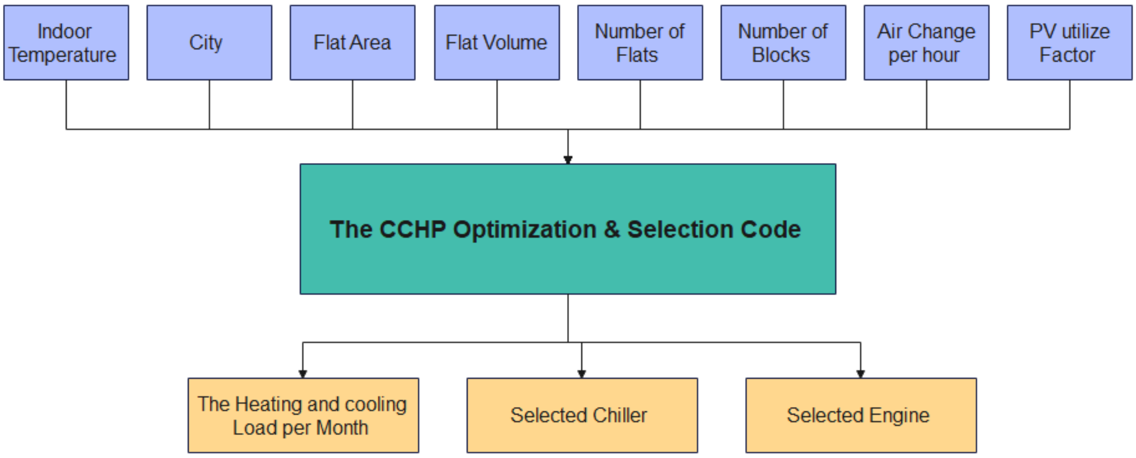

Fig. 5. The code structure for the hierarchy of inputs and outputs with multiple inputs

5. RESULTS AND DISCUSSION

5.1 Case 1: Alexandria Indoor Temperature 22°C

The simulation of a condominium complex in Alexandria, Figs. 6 and 7, involves 60 units with a 150 m^2 area and 450 m^3 volume, with an air changes per hour (ACH) rate of 0.6 and a target indoor temperature of 22°C. The structure is made of concrete and has 60 units distributed among five building blocks. The PV system installs solar panels on 40% of the roof surface. With a 2-kW electrical load per unit, the monthly total electrical load is 600 kW. In August, the cooling load varies to 3.1 kW. The specified loads determine which chillers are selected; the 047B model has the largest cooling capacity. With 793 kW of electrical power and 1104 kW of thermal energy, the NG 260 engine is chosen to power the building, guaranteeing that its electrical and cooling requirements are satisfied all year long.

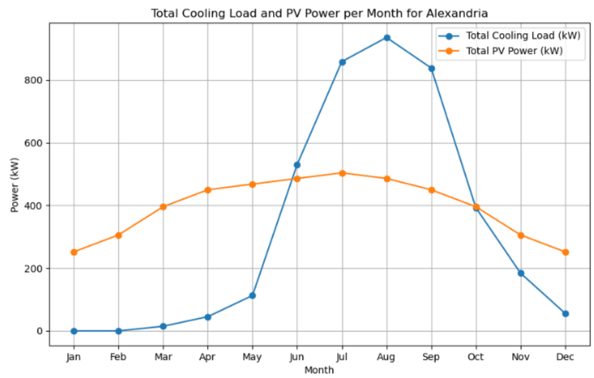

Fig. 6. PV and cooling load for case 1

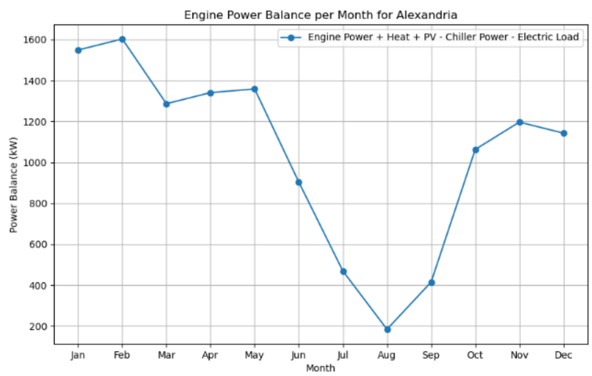

Fig. 7. Case one - excess power

5.2 Case 2: Alexandria Indoor Temperature 25°C

A simulation of a condominium building in Alexandria, Figs. 8 and 9 were conducted using input data. The building has 60 units spread across five blocks, with a PV system using 40% of the roof area for solar energy generation. Each unit has an electrical load of 2 kW, resulting in a total monthly electrical load of 600 kW. The cooling load varies throughout the year, with the highest load occurring in July and the lowest in May. The 021B chiller model is chosen for its cooling capacity, with 498 kW required during July, the peak cooling demand month. The EM-430/580 engine is used, providing 435 kW electric and 614 kW thermal output, ensuring both cooling and electric demands are met throughout the year.

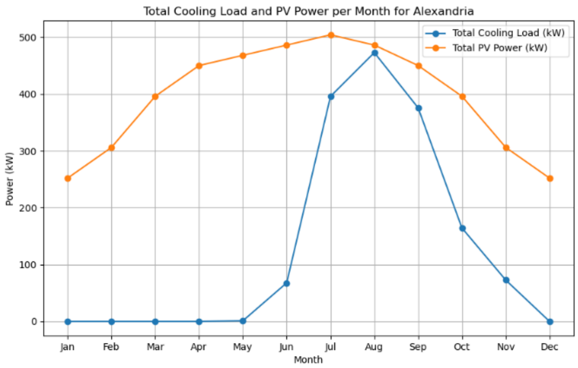

Fig. 8. PV and cooling load for case 2

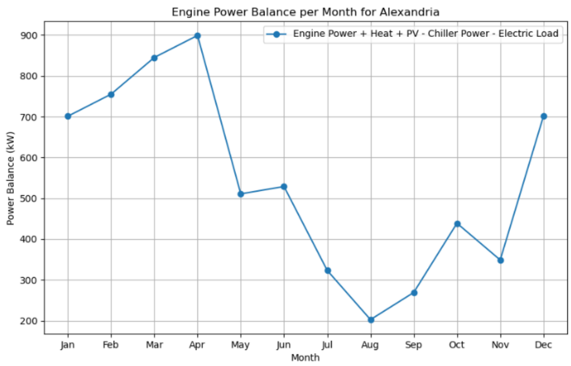

Fig. 9. Excess power for case 2

5.3 Case 3: Kuwait with an Indoor Temperature of 22°C

Kuwait City's cooling and energy system consists of 60 units across five building blocks, each with a 450 m^3 volume (Figs. 10 and 11). The in-room temperature is 22°C, and the peak PV power output is 468 kW in June. The peak cooling load occurs in August, with an aggregate cooling requirement of 2810.1 kW. The system utilizes the largest available chiller, 052A, with a cooling capacity of 2135 kW, and a second chiller, 030B, with a capacity of 703 kW. The system features three EM-530/660 engines, with a total electric output of 1853 kW and a thermal output of 2480 kW. The system's peak surplus power is observed in January, with a power surplus of 4003 kW.

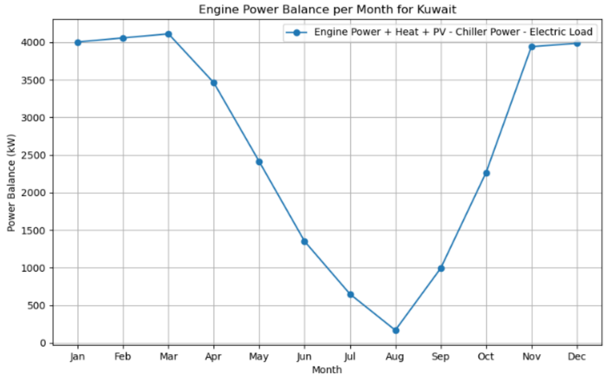

Fig. 10. Excess power for case 3

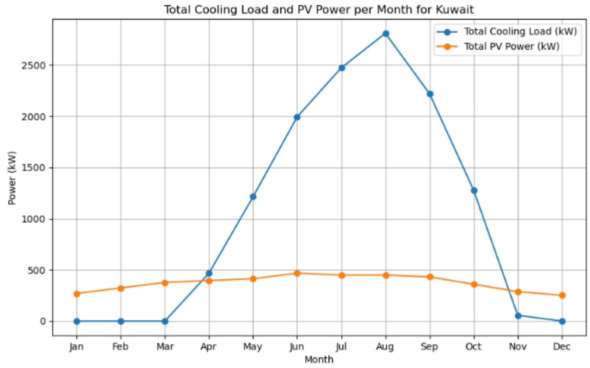

Fig. 11. PV and cooling load for case 3

5.4 Case 4: Calgary and Heating Alternatives

Calgary's buildings experience a steady need for heating due to cold weather, with the highest heating load in January reaching 3,360 kW. The building's PV power generation helps meet energy needs, but its output remains low throughout the year, as shown in Figs. 12 and 13. In July, it reaches a peak of 432 kW, which is typical for Calgary due to the increased sunshine in the summer. The most significant difference between the heating load and PV power is evident in winter, when the load reaches 3360 kW, while the PV system produces only 108 kW. The EM-430/580 CHP engine is chosen to bridge the gap between heating load and PV power, delivering 1,495 kW of electricity and 1,990 kW of heat. The CHP engine is crucial as it compensates for the lack of energy from PV panels, meeting the building's electricity and thermal needs year-round.

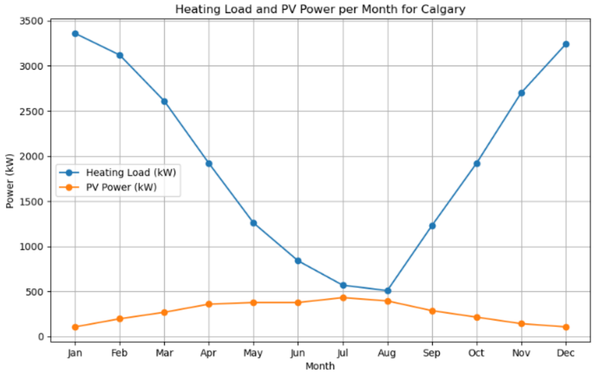

Fig. 12. PV and heating for case 4

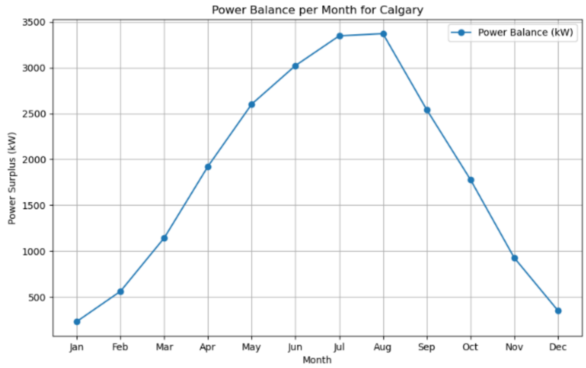

Fig. 13. Excess power for case 4

Table 1. Detailed summary of mean results from case studies

Case study	Peak load (kW) (cooling/heating)	PV power contribution (kW)	Electric load (kW)	Selected chillers	Chiller capacities (kW)	Selected engines	Engine power (kW)	Engine heat (kW)	Power surplus (kW)
Alexandria (22°C)	935.5 (cooling, Aug)	504	600	047b	1055	Ng 260, EM -530/660	793	1104	184.5 (Aug)
Alexandria (25°C)	472.8 (cooling, Aug)	504	600	021b	498	EM-430/580	435	614	202.6 (Aug)
Kuwait (22°C)	2810.1 (cooling, Aug)	468	600	052a, 030B	2838	3x EM-530/660, ng 260	1853	2480	168.6 (Aug)
Calgary (heating)	3360 (heating, Jan)	432	600	N/A (heating)	N/A	EM-430/580	1495	1990	233 (Jan)

5.5 Discussion

This study emphasizes the versatility and efficacy of the created CCHP microgrid simulation code in handling various meteorological and operational conditions. The code automatically modifies cooling and heating outputs based on actual manufacturer data for chillers and engines in cities including Alexandria, Kuwait, and Calgary. For instance, Alexandria's cooling load in August at 22°C necessitated the largest chiller (047b) and a combination of NG 260 and EM-530/660 engines, resulting in a power surplus of 184.5 kW. Conversely, at 25°C, the cooling demand was reduced by half, requiring less equipment with a 202.6 kW surplus. The extreme temperatures in Kuwait required many chillers and engines to handle a peak cooling load of 2810.1 kW. Conversely, Calgary's heating demands in January were adequately met by the EM-430/580 engine, yielding a surplus of 233 kW.

By combining data on solar radiation and weather with cooling and heating requirements, the methodology improves equipment selection and ensures that energy solutions are tailored to specific operating and climatic conditions. To counteract seasonal variations, monthly power balance assessments highlight the use of renewable energy with combined heat and power systems. The simulation is a vital tool for designing effective and sustainable microgrid systems because of its dynamic and modular methodology, which ensures its applicability in a wide range of contexts.

5.6 Validation and Comparison to a Similar Study

The suggested hybrid PV-CHP optimization model's validity is based on its conceptual uniqueness, practical design, and conformity to accepted methodologies. The current research provides a stand-alone, open-source framework that directly integrates real manufacturer specifications with user-defined parameters and climatic data, in contrast to earlier studies that rely on abstract representations or multi-software integrations (e.g., Xu Wang et al., 2022 [16]). By allowing for monthly adjustments based on actual solar irradiance, ambient temperature, and load variations, this integration marks a significant advancement in the modelling of CCHP systems. In contrast to static or annual-average models, the unique feature is the monthly dynamic reconfiguration of system components, which guarantees greater responsiveness to seasonal variations. Additionally, because of the model's architecture, which prioritizes transparency and adaptability, engineers and researchers can use real-world catalogues to simulate region-specific conditions. The model's realism and legitimacy as a validation tool are increased by using real equipment data from Viessmann CHP engines [14] and carrier chillers [15], as well as PV performance calculated from NREL's PVWatts calculator and datasets [11, 12]. Its academic rigor and engineering applicability are supported by its capacity to quantify seasonal surpluses or deficits, optimize component selection, and dynamically simulate energy balances. Future validation attempts should use different manufacturer datasets, like those from Yanmar or Capstone microturbines, and absorption chillers from Trane or Thermax to increase the model's robustness and generalizability. The Model Equations are extracted from the references in [17-27].

A comparative investigation of equipment kinds and regional climates would assess the model's sensitivity and broaden its applicability in commercial and industrial contexts. This would further solidify the framework as a universally applicable instrument for optimizing hybrid energy systems.

6. CONCLUSION

Superior efficiency in controlling energy demands under a variety of climatic conditions is demonstrated by the Python-based model created for CCHP microgrid optimization. Real manufacturer data for engines and chillers further improves the model's performance. The code includes an automated selection feature that enables either cooling or heating mode depending on the city's annual peak temperature, thereby increasing system adaptability across different climate zones.

This study introduces a dynamic, code-driven optimization methodology for CCHP systems, validated through detailed case studies in Alexandria, Kuwait, and Calgary. The core numerical findings reflect the practical applicability of the proposed model.

- Alexandria (22°C): In August, the maximum cooling load reached 935.5 kW. The system utilized the 047b chiller, with a capacity of 1,055 kW, and the NG 260 engine, which generated 793 kW of electrical power and 1,104 kW of thermal power. A surplus power of 184.5 kW was recorded.
- Alexandria (25°C): at this higher indoor temperature setpoint, the August cooling load decreased by 50% to 472.8 kW. This reduction enabled the use of the smaller 021b chiller (498 kW capacity) and the EM-430/580 engine, which supplied 435 kW of electrical power and 614 kW of thermal output. The resulting power surplus was 202.6 kW.
- Kuwait (22°C): due to harsh summer conditions, the August cooling load peaked at 2810.1 kW. The model selected two chillers – 052a (2,135 kW) and 030B (703 kW) – alongside three EM-530/660 engines, producing a total of 1,853 kW in electrical power and 2,480 kW in thermal energy. January exhibited a system power surplus of 4003 kW.
- Calgary (heating mode): during peak heating demand in January, the system utilized the Em-430/580 engine to meet a 3360-kW load. The engine produced 1495 kW of electrical and 1990 kW of thermal output, yielding a surplus of 233 kW.
- A key outcome of this study is the transition from theoretical modelling to a more applied engineering approach. By incorporating authentic manufacturer data, the methodology enables precise equipment optimization based on actual performance metrics. The model accounts for seasonal variability and geographic specificity, aligning with real-world engineering workflows.

The system demonstrates robust energy surplus management in all tested cases, ensuring an optimal balance between equipment coordination and energy redistribution. By matching engine heat output with chiller capacity, it provides efficient operation and component compatibility. This practical framework lays the groundwork for future software platforms integrating multi-vendor data, reinforcing the model's scalability and applicability in real-world CCHP microgrid optimization.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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