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OPTIMAL CONTROL STRATEGY OF POWER GENERATION IN MICROGRIDS

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Lucrarea prezinta o soluție inovativă de strategie de control optimal pentru un sistem energetic care constă în combinarea energiei termice și electrice (Combining Heat and Power - CHP) cu interconectarea surselor de energie regenerabilă (Renewable Energy Sources - RES), permițând generare hibridă eficientă de energie. Necesarul de energie electrică și termică al consumatorului este controlat prin intermediul unui sistem dedicat de microrețea (microgrid - MG). Strategia de optimizare a fost validata prin controlul sistemului HVAC al unei clădiri și își propune să satisfacă două obiective principale: i) reducerea la minim a energiei absorbite din rețeaua electrică tradițională și ii) garantarea unor condiții acceptabile de confort termic. Programul de răspuns la cerere propus este o strategie de control cu feedback parametrizat în care parametrii depind de starea termică a clădirii, dar și de modelul de ocupare al microrețelei.

The paper presents an innovative optimal control strategy solution for an energy system that consists of combining thermal and electrical energy (Combining Heat and Power - CHP) with the interconnection of Renewable Energy Sources - RES, allowing efficient hybrid energy generation. The consumer's electricity and thermal energy needs are controlled by means of a dedicated microgrid system (MG). The optimization strategy was validated by controlling the HVAC system of a building and aims to satisfy two main objectives: i) minimizing the energy absorbed from the traditional electrical network and ii) guaranteeing acceptable thermal comfort conditions. The proposed demand response program is a parameterized feedback control strategy where the parameters depend on the thermal state of the building, but also on the occupancy pattern of the microgrid.

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1. Introduction.

The innovation consists in combining heat and power (CHP) with the interconnection of renewable energy sources (RES) allowing microgrid to provide an effective hybrid generation. Focusing on the electricity and thermal energy requirement of contemporary buildings, a joint operation of photovoltaic/thermal (PV/T) based prosumers is controlled by means of a dedicated microgrid (MG) system. The bidirectional flow of the electricity and heat model is considered and

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is optimally managed using a price-based demand response (DR) scheme. The objective functions of both the prosumer and MG operator (MGO) are formulated as a profit maximization problem where they interact with each other on the basis of DR activity. To establish this strategic decision-making process, the system is modelled as an equilibrium game, where MGO acts as a leader while PV/T prosumers act as a follower.

A MG based Combined Heat and Power (CHP) system is regarded as one of the primary Distributed Energy Resources (DER) in the microgrid (MG). With the ability to generate both electricity and heat, CHP system is a special type of DER that has advantages in controllable, economic, and environmental benefits. Generally, there are two common operating strategies for the CHP system: Following Electric Load (FEL) and Following Thermal Load (FTL) [1]. In order to achieve the optimizing operation, optimal energy management is essential for the operation of CHP-based MGs. In a traditional MG, the end users of the electricity and heating are usually seen as passive consumers. That is, Microgrid Operator (MGO) can directly decide the operation strategy according to the total energy demand of users. The operation goal is to maximize economic benefits or minimize generation cost [2]. Until recently, there have been numerous studies focused on the operation of CHP-MG, including feasibility analysis, control model and optimal scheduling. An optimized CHP system must cover primary energy savings as well as reducing the emissions. Generally, primary energy consumption, operation cost or profit are employed to show the cost efficiency of CHP system. Thus, to cover the various aspects as highlighted in the aforementioned studies, an energy management system (EMS) is designed for the system to analyse the economic benefits.

2. Modeling CHP-MG architecture and energy flows

The grid-connected CHP-MG structure is shown in Fig.1. The cogeneration system consists of three mains energy sources: electricity (Power Bus), thermal energy (Thermal Bus) and natural gas (Gas Bus), the latter being used only in extreme situations where it was not possible to connect to the network main electrical. In principle, the power required for consumers is provided by renewable energy sources: 1) Photovoltaic power plant with around 500 photovoltaic panels; 2) Thermal plant with solar panels; 3) The plant that provides energy from geothermal resources. As I already said, there is also a gas-fired thermal power plant, used only as a back-up. For the future, it is planned to use photovoltaic panels that will also provide heat, the so-called PV/T system. Electrical energy consumers are separated from thermal energy sources, but can be included in the HVAC (Heating, ventilation, and air conditioning) category.

Generally, the CHP system is controlled by the MGO, which has the privilege to decide the mode of operation and the power generation plan. In the user side of MG, it is considered that each user should be implemented with Building Energy Management System (BEMS) [3]. BEMS can collect data on users' electrical and thermal load and receive price information from MGO. In addition, it handles the control and optimization of users' energy consumption.

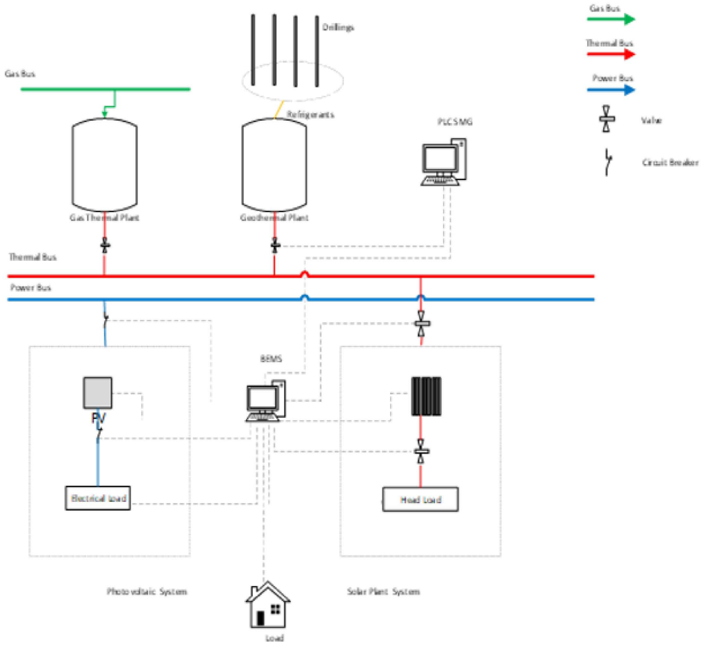
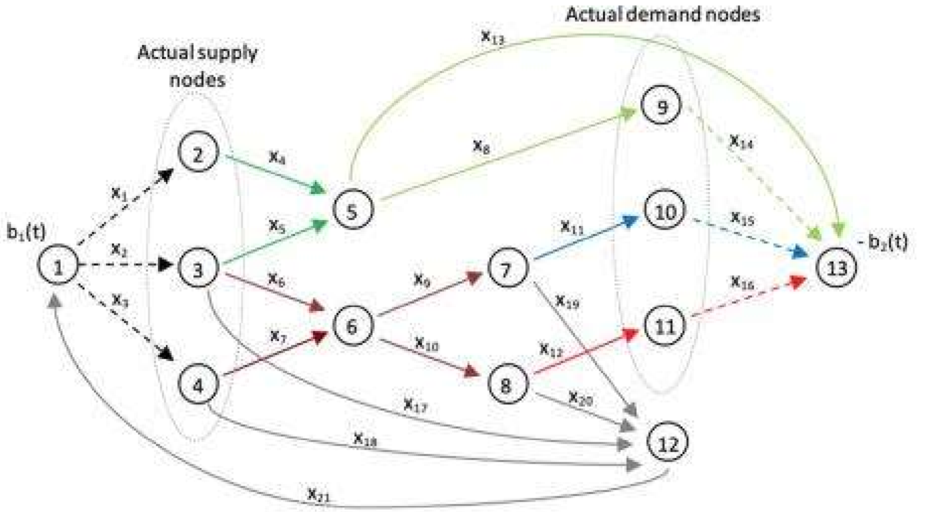


Fig.1. Block diagram of the CHP-MG system

For a more general application, CHP systems are designed to utilize the heat energy from an on-site power generation unit (PGU) so that it can satisfy both the electric and thermal load at the same time in an effective manner, energy recovery components, which are used to recover useful heat and energy management system, which regulates the operation of the system. In addition, CHP systems provide solutions to reduce electricity grid dependence and save energy costs. Fig.2 shows a detailed diagram of the energy flows in a CHP-MG system. The scheme, taken from the literature [4], is general, but fully covers the application in this work.



Node 1: Total energy supply, $b_1(t)$
Node 2: Electric Grid (EG)
Node 3: Cogeneration Systems (CS)
Node 4: Supplementary Heating Devices (SHD)
Node 5: Electric energy provided from CS and EG
Node 6: Thermal energy provided from CS and SHD
Node 7: CHP cooling components
Node 8: CHP heating components
Node 9: Electric energy demand
Node 10: Cooling energy demand
Node 11: Heating energy demand
Node 12: Total energy loss
Node 13: Total energy demand, $b_2(t)$

x_1: Electric energy supply
x_2, x_3: Fuel energy supply into CS and SHD
x_4, x_5: Electric energy flow from EG and CS
x_6, x_7: Thermal energy flow from CS and SHD
x_8: Electric energy flow into CHP building
x_9, x_{10}: Thermal energy flow into CHP components
x_{11}: Cooling energy flow into CHP building
x_{12}: Heating energy flow into CHP building
x_{13}: Excess electric energy flow export to EG
x_{14}, x_{15}, x_{16}: Electric, cooling, and heating energy demands
x_{17}, x_{18}, x_{19}, x_{20}: Energy loss
x_{21}: Total energy loss

Fig.2. Network flow model of a typical CHP-MG cogeneration system (after [4])

Combined heat and power (CHP) with RSE interconnection have marked a breakthrough by providing an efficient hybrid power generating source. The most promising hybrid solution is photovoltaic/thermal (PV/T) panels. It uses thermal collectors on a traditional PV panel to capture heat from the surface of the PV panel, thus improving electrical efficiency [5] and producing additional heat for local use. The concept of net zero energy building [6] has also emerged where the user can now meet their heat requirements locally with the PV/T panel on the roof, which is again the best solution for buildings where space restriction is a major bottleneck. For the operation of the cogeneration system, three operating strategies have been proposed, which either have as the leader the electric energy source (FEL), or the thermal energy source (FTL) or even a hybrid leadership (Following Hybrid Load - FHL) [7]. Since the CHP system is capable of generating both electricity and heat, its operating criteria are subject to the form of energy required by the user. The possible operating strategies of the CHP system are presented in Table 1. Case 1 describes the idle state of the MV, case 2 represents a system where the MV is operated in heat-driven mode regardless of the electricity demand which is then met by the grid of utilities. Case 3 is the opposite, i.e. the electrically driven mode. Case 4 is the hybrid mode of the CHP system where the MGO can switch between FTL and FEL modes.

Table 1 Operating strategies of CHP

Case	E Electrical demand	Heat demand	CHP mode
1	no	no	off
2	no	yes	FTL
3	yes	no	FEL
4	yes	yes	FHL

3. Microgrid control

3.1. General considerations

Microgrid control is a complex and many-layered topic. The first decisions a researcher or microgrid implementer must make are related to the structure of the control architecture –whether it will be centralized, distributed, or somewhere in between; how the control hierarchy will be arranged (if any exists); and whether the controller will perform supply side management (such as voltage and frequency regulation) or demand side management, or both. As previously mentioned, this paper will focus exclusively on microgrid energy management systems for demand side. The second layer of microgrid control is the control strategy. There are four main control strategies that appear in literature: rule-based control (RBC), optimal control, agent-based modeling (ABM), and model predictive control (MPC). Finally, the innermost layer of microgrid control is the actual solving of optimization problems, which can be done through one of several methods.

In the broadest sense, the goal of any microgrid control problem is to minimize the overall operational cost of the microgrid while satisfying various constraints including occupant satisfaction, equipment limitations, and grid reliability. The problem in its most general form is expressed as $\min \sum_j f_j\,(x, u)$ where $x \in X$ contains the states of the various microgrid components, $u \in U$ contains the control decisions to be made, and $f_j(x,u)$ are the various costs and penalties which should be minimized.

3.1.1 Centralized vs. Distributed

As the name suggests, a centrally controlled Energy Management System (EMS) gathers data from all components into a central processing, computing, and controlling unit, named in the following Microgrid Operator (MGO). The central unit uses the input data to solve the optimization problem; it outputs the optimal control decisions, and then the decisions are transmitted to the various components of the EMS, where they are implemented. In a distributed control scheme, multiple distributed agents solve their own optimization problems without knowledge of the other agents. Then, a central agent collects the individual solutions and uses them to make centralized decisions, sending those centralized decisions to the distributed agents for implementation. In a completely decentralized control structure, different microgrid components make localized control decisions without having access to data from all of the other components. The difference between distributed and decentralized control schemes is that in a decentralized control scheme, there is no central agent to aggregate the local decisions and perform an optimization over the whole system. Agent-based modeling typically follows a decentralized control scheme, for instance. Each agent is concerned only with making its own decisions to further its own interests, and while different agents must necessarily interact with one another, there is often no central optimizing agent. Rather, central agents act as coordinators between the individual component agents. Centralized control is well-suited for small microgrids with few components. It is also easy to implement due to the fact that there is no need for coordination or extensive communication among members. However, centralized control has the disadvantage of having a single point of failure, whereas distributed control is more resilient in that regard. Additionally, the larger a microgrid grows, the more difficult it becomes to incorporate new components into a central controller. For large microgrids, the computational cost of complex optimization problems may also become an issue. For this reason, distributed and decentralized control structures are better suited to large systems with many components, especially when the microgrid is expected to be expanded in the future.

3.1.2 Hierarchies

Hierarchical microgrid control structures can be advantageous due to the large number of functions the controller must perform, from voltage and frequency control to short-term forecasting to communication with the grid to problem solving and making decisions. However, there is a potential for introducing unnecessary complexity, since different layers in a hierarchy must communicate with each other, increasing the communications burden and possibly outweighing the positive effects. In the most utilized EMS hierarchy there are three layers – the execution control layer (ECL), optimizing control layer (OCL), and supervisory control layer (SuCL). The OCL generates the control trajectory for the ECL; the ECL is responsible for implementing the control decisions received from the OCL; the SuCL is responsible for interlayer coordination, soft switching between operational modes, and control strategy selection. A hierarchical architecture allows to handle the uncertainty of renewable energy sources and realize an economic generation schedule for a microgrid, actually two stages of scheduling – day-ahead and several hours-ahead. Each scheduling stage contains two levels: the lower level finds a joint output of the microgrid's renewable energy systems, which it passes to the upper level. The upper level uses this information to optimally determine the generation schedule of dispatchable generators.

3.2 Control Strategies

Figure 3 shows how the four control strategies previously mentioned compare to each other in terms of complexity and effectiveness at achieving energy and cost saving goals. In the figure, *n* is the number of microgrid components present in the model.

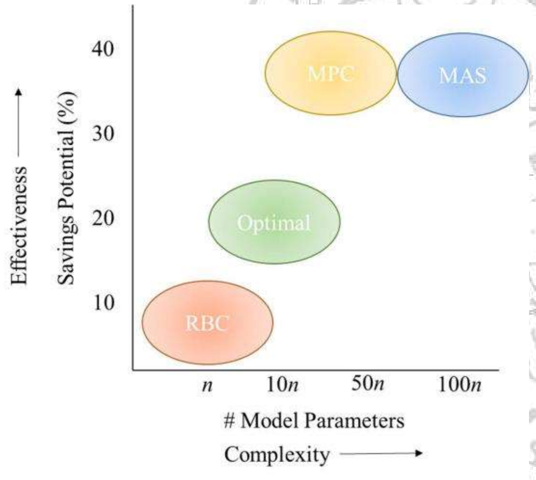


Fig.3. Comparison between different control strategies (after [8])

The vast majority of implemented solutions use optimal and model predictive control strategies. For the purposes of our project, optimal control offers the best ratio between effectiveness and complexity. In optimal control, control decisions are made simply by solving an optimization problem and implementing its optimal control result. The goal of an optimization problem is to optimize (minimize or maximize) an objective by varying the values of decision variables while satisfying a set of constraints.

In virtually all studies that involve optimization, the objective is to minimize the total operational cost of the microgrid. This total cost can include many different components – most commonly, the cost to purchase power from the grid. Other included components may pertain to the cost of energy generation by conventional means, energy storage costs, and equipment maintenance costs. The objective can also contain penalties for undesirable actions – for example, task interruptions in a DR. Table 2 summarizes the most frequent objective functions that appear in the reviewed microgrid literature.

Table 2. Objective functions

Objective	Typical Equation	Details
Energy purchase cost	$\sum_{\mathrm{i}} C \cdot P_{grid,\mathrm{i}}$	Total cost of energy purchased from the powergrid
Operational cost	$\sum_{\mathrm{i}} C_{ope,\mathrm{i}} \cdot P_{G,\mathrm{i}}$	Cost of operating generators
Maintenance cost	$\sum_{\mathrm{i}} C_{mnt,\mathrm{i}} \cdot P_{G,\mathrm{i}}$	Cost of maintaining generators
Comfort penalty	$\sum_{\mathrm{i}} C_{com,\mathrm{i}} \cdot \lvert T_{in} - T_{bnd}\rvert^2$	Penalty applied to limit temperature violations
Demand-response cost	$\sum_{\mathrm{i}} C_{curt} \cdot t_{curt,\mathrm{i}}$	Penalty applied to limit total load curtailment time

The meaning of the variables in the formulas: C- cost of energy purchase (Lei/kW); $Pgrid$,i - power purchased from grid (kW); $P_{G,\mathrm{I}}$ - power output of generator i (kW); Tin - indoor temperature (°C); T_{bnd} - setpoint(bound) temperature (°C); $t_{curt,i}$ - total load curtailment time (hr)

Often, optimization problems have more than one objective. In several studies, multi-objective optimization (MO) is performed with harmfull emissions limiting being the second objective. In a few others, occupant thermal comfort is taken as the second objective. Multi-objective optimization is obviously useful when there are two separate quantities of interest (e.g., total cost and pollutant emissions). However, the nature of MO is such that no single solution exists which simultaneously optimizes every objective because the different objectives often compete with each other. For instance, for our study we decide to perform MO with two objectives: minimize cost and maximize thermal comfort, but a solution that increases thermal comfort may indicate greater power usage and therefore greater cost. This competition between objectives means that in a MO problem, a decision must be made as to the relative importance of the objectives. To do this, one can include weighting factors in the objective functions. The higher the weighting factor, the more important it is to minimize that particular objective.

4. Proposed optimization solution

This project presents a novel control algorithm for joint demand response management and thermal comfort optimization in microgrids equipped with renewable energy sources associated in a CHP system. In order to simplify the control procedure, the optimization solution presented in the following aims to satisfy only two main objectives:

1) Thermal and occupancy information in microgrids: demand response is achieved by controlling the HVAC system of a building; the final objective is not only the reduction of the energy absorbed from the traditional electrical grid, but also guaranteeing acceptable thermal comfort conditions. The proposed demand response program is a parametrized feedback control strategy where the parameters are dependent on the thermal state of the building, but also on the occupancy pattern of the microgrid.

2) Scalability to large microgrids: from the control perspective, a microgrid is a large-scale dynamic system with high complexity and a huge amount of information. In order to address the computational complexity, the proposed control strategy adopt a two-level supervisory strategy: at the lower level, each building employs a local controller that processes only local measurements; at the upper level, a centralized unit supervises and updates the PLC controllers with the aim of minimizing the aggregate energy cost and thermal discomfort of the microgrid. This architecture is supposed to be scalable to microgrids composed of many buildings.

Control objectives

The first objective is to reduce energy costs: this is achieved if the energy available from the renewable sources is exploited to the maximum extent. The problem is not trivial since the renewable energy is available depending on weather conditions. A particularity of the MG for which the optimization solution was designed is that no energy storage device is used. This solution is explained by the fact that the daily energy consumption can be estimated in advance with sufficient precision. The purpose of the scheduling is to use the electricity from the main grid only as a back-up solution for critical situations, the rest being the energy obtained from renewable sources, the electricity from photovoltaic panels (PV), the heat from solar panels and from geothermal wells. Only when the sum of renewable energy is not enough, extra energy can be absorbed from the main grid. On the other hand, if the energy that the renewable sources produce is in excess compared to basic microgrid energetic needs, auxiliary load (eg. auxiliary boiler) take this surplus. It is crucial to fully take advantage of renewable energy when available in order to enable the 'islanded mode' (standalone) of the microgrid and minimize the dependence from the main grid. The demand response is regulated by regulating the HVAC operation: the HVAC operation has a direct impact not only on energy demand, but also on the thermal comfort of the occupants. If one objective of the demand response program is to reduce energy costs, another objective is to manage the HVAC operation so as to satisfy the thermal comfort of the users. The two objectives are expressed by a suitable performance index as explained hereafter.

Performance Index

The performance index to be optimized takes into account two terms: the energy cost and the thermal comfort of the occupants. At time *t* the aggregate performance index of the microgrid is defined as:

$$M(t) + \sum_{i=1}^{n}(k \times E_i(t) + (1-k) \times C_i(t)) \quad (2)$$

where E_i is the energy score and C_i the thermal comfort score of building *i* and *n* is the number of buildings serviced by MG. The energy and the comfort score are, typically scaled, so as to be of the same order of magnitude and contribute fairly to the total score. According to the importance that the designer wants to give to a term with respect to the other, the summation can be weighted using the scaling factor $0 < k < 1$.

Each local optimization algorithm employs a controller based on a local feedback vectors, whose structure contains data on external weather conditions (outside temperature, outside humidity and solar radiation), *n* temperatures of the thermal zones, *n* humidities of the thermal zones, *n* set points of the HVAC devices in the thermal zones and *n* detectors of occupancy in the thermal zones (*n* is the number of thermal zones).

Hereafter we explain with more details the choice of the feedback vector: the zone temperature and humidity are a natural choice for the thermal state of the building; outdoor weather conditions both in the present and the future help to achieve a pro-active control strategy. Finally, the information about the occupancy of a thermal zone is provided as a feedback component to the control strategy. The occupancy signals are important also for another reason. A frequent problem in building management is the creation of comfortable conditions just before people start using the building. In order to achieve this, many control strategy uses a training period to ”learn” the occupancy schedule. Using the PCAO algorithm, as presented above, a double feedback loop procedure runs in each building. The primary feedback loop runs in real-time, with actions applied to the actual building and measurements collected. In parallel with the primary loop, a secondary simulation-based loop interacts with the energetic model of the building, in order to find better strategies at the next time step. With the term ‘simulation-based’ design we refer to a method where the optimization of the cost function involves an iterative process of system simulation/controller redesign. At this point is crucial to introduce and explain two-time metrics: the control horizon and the simulation horizon. By control horizon we refer to the time interval of HVAC management. For example, in our test cases, the HVAC set points are changed by the algorithm every 10 minutes. On the other hand, as a simulation horizon we refer to the whole duration of the experiment. Usually, as a simulation horizon we refer to one day. This two-loop design is implemented in each building separately. The secondary loop operates in order to find a better controller for the real system. Simultaneously, the primary loop/system, uses the best so-far controller to manage the HVAC.

The purpose of this work is to provide a control architecture that that be scalable to an arbitrary number *n* of buildings: for this reason, a centralized control architecture was discarded and the following bi-level supervisory strategy was implemented for the control and manipulation of each building/HVAC unit of the microgrid. The two levels can be identified as: a local building level and an aggregate microgrid level. In the simulations the controllers, one for each building, operate using only local information plus information about weather forecast. At the aggregate level a supervisor takes into account the performance of each building and calculates the total cost, so as to optimize the global performance of the microgrid. As compared to a fully centralized strategy, the computational and communication requirements of the proposed control architecture are reduced. The goal of each optimization algorithm is to optimize the performance of the building by taking into account only local information such as the thermal state of the building, occupancy information, and weather conditions. Each local controller communicates with the central node and offer information about the cost that the proposed control strategy is achieving and achieved in the past. The central node concentrates this information from each different building, calculates the total cost and decides if the ‘team’ of controllers achieved the best aggregate performance.

Fig. 4 presents the proposed control architecture around a central SCADA server.

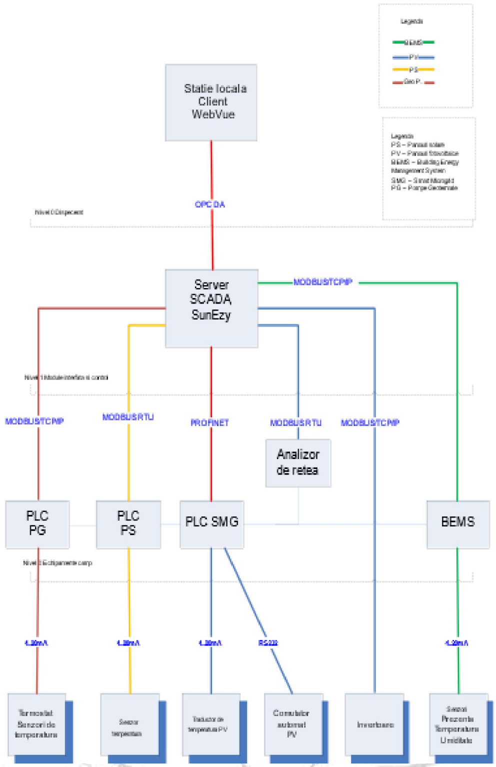


Fig.4. Implementation of the control architecture.

5. Conclusions

In this paper, we presented how Combined Heat and Power (CHP) can play a central role in microgrid development and widescale adoption by providing reliability and resilience, and ensuring continuous operation for host facilities, in a specific application including buildings and campuses. In order to improve the grid penetration of renewable energy and reduce the fluctuation of grid-connected power generation process, this paper combines various RES to form a complementary power generation system. In addition a bi-objective optimal scheduling strategy is proposed. The economic operation of a microgrid is achieved through an energy management system that optimally schedules several distributed power generation devices and continuously balances supply and demand. The effectiveness of the models was verified on a control architecture around a central SCADA server.

REFERENCES

[1] Hannan, M. A., Tan, S. Y., Al-Shetwi, A. Q., Jern, K. P., & Begum, R. A., Optimized controller for renewable energy sources integration into microgrid: Functions, constraints and suggestions. Journal of Cleaner Production, 256, 2020

[2] Cecilia, A., Carroquino, J., Roda, V., Costa-Castelló, R., & Barreras, F., Optimal Energy Management in a Standalone Microgrid, with Photovoltaic Generation, Short-Term Storage, and Hydrogen Production. Energies, 13(6), 1454, 2020

[3] N. Liu, L. He, X. Yu, L. Ma, Multiparty Energy Management for Grid-Connected Microgrids With Heat- and Electricity-Coupled Demand Response, IEEE Transactions on Industrial Informatics, vol. 14, no. 5, pp. 1887-1897, 2018

[4] Zhang, J., Cho, H., Mago, P., Energy conversion systems and Energy storage systems, book: Energy Services Fundamentals and Financing, pp. 155-179, 2021

[5] Zhang, L. et al, Optimal Energy Management for Microgrids with Combined Heat and Power (CHP) Generation, Energy Storages, and Renewable Energy Sources, Energies, 10(9):1288, 2017

[6] Kermani, M., et al, A Nearly Zero-Energy Microgrid Testbed Laboratory: Centralized Control Strategy Based on SCADA System, Energies, 13:2106, 2020

[7] Ali, A., Liu, N., Li, H., Multi-Party Energy Management and Economics of Integrated Energy Microgrid with PV/T and CHP system, Renewable Power Generation, IET 13(3), 2019

[8]. Fontenot, H., Dong, Bi., Modeling and control of building-integrated microgrids for optimal energy management – A review, Applied Energy, Elsevier, vol. 254(C), 2019