

A Demand-Responsive Multi-Energy System Framework Integrating Flexible Pricing for Improved Urban Energy Management

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Abstract—This paper proposes a bi-level optimization framework for dynamic pricing in multi-energy systems (MES), addressing the interaction between energy retailers and consumers in urban environments. The model employs a hierarchical structure where a multi-energy service provider (MESP) optimizes profit through dynamic pricing in the upper level, while consumers respond to these signals by adjusting their thermal loads and shifting their electrical loads in the lower level. The bi-level problem is reformulated into a tractable single-level optimization using Karush-Kuhn-Tucker (KKT) conditions. The results demonstrate that the proposed approach effectively reduces peak demand and operational costs by 14.8%, contributing to more sustainable urban energy systems.

Keywords— *Multi-energy system, Demand response, Multi-energy service provider, Energy trading, Energy pricing*

I. INTRODUCTION

The evolution of building energy systems has led to the emergence of multi-energy buildings capable of managing both electrical and thermal energy demands efficiently [1]. This transformation has expanded the traditional concept of demand response (DR) beyond simple load shifting or reduction. In multi-energy buildings, consumers can now optimize their energy consumption patterns across multiple energy vectors, responding to price signals through both electrical and thermal systems [2]. This enhanced flexibility in demand response creates opportunities for more sophisticated pricing mechanisms that can benefit both retailers and consumers.

Price-based DR (PBDR) has emerged as a particularly effective approach for managing energy consumption in multi-energy buildings [2]. Through dynamic pricing signals, retailers can influence both electrical and thermal consumption patterns, while consumers can reduce their energy costs by adjusting their usage according to these price signals. However, determining optimal retail prices that balance retailer profits with consumer benefits remains a complex challenge.

Various approaches have been proposed, from transactive pricing schemes with quadratic utility functions [3] to data-driven methods using price-demand elasticity matrices [4], [5]. However, most existing studies treat the response characteristic

as a predetermined function, which may not accurately reflect the complex interactions between electrical and thermal systems in multi-energy buildings. The actual response characteristics are often non-analytic and highly dependent on both electrical and thermal retail prices.

Different methodologies have been employed to capture these complex response characteristics. Some researchers have used discrete testing approaches [6]–[8], while others have developed more sophisticated methods using Lagrange functions [9] or machine learning techniques [10]. However, these approaches often focus on static characteristics within single time intervals, overlooking the temporal coupling effects that arise from energy storage systems and in some cases the building thermal dynamics.

The interaction between retailers and consumers in multi-energy systems has been modeled using various game-theoretic approaches [11]–[14] and hierarchical optimization methods [15]–[17]. While these studies have provided valuable insights, they often simplify either the network constraints or the multi-energy aspects of building operations. Additionally, most existing work [15]–[19] has focused primarily on electrical demand response without fully incorporating the thermal loads in pricing scheme.

To address these limitations, this paper proposes a bi-level retail pricing strategy that explicitly considers both electrical and thermal demand response in MES. The upper level represents the retailer's profit maximization problem, while the lower level captures the consumers' cost minimization objectives for both electrical and thermal energy. It distinguishes between adjustable thermal loads and shiftable electrical loads with non-shiftable electrical loads recognizing their different operational characteristics and constraints. The resulting comprehensive framework enables optimization of energy pricing in buildings' MES while maintaining computational tractability through appropriate reformulation techniques.

II. PROPOSED METHODOLOGY

This paper proposes a novel bi-level optimization framework for dynamic energy pricing in multi-energy buildings that explicitly accounts for the distinct characteristics of electrical and thermal demand response. The overview of the proposed

framework is depicted in Figure 1. In the upper level, the retailer determines optimal time-varying prices for both electricity and thermal energy to maximize their profit while considering network constraints and wholesale market conditions. The lower level encompasses multiple building energy management systems, where each consumer optimizes their electrical and thermal consumption in response to the retailer's price signals. This paper mainly focuses on the optimization process rather than the practicality of automated engagement of the process enabled via consumers. A key innovation of our approach is the differentiated treatment of thermal and electrical loads: thermal demands are modeled as adjustable but non-shiftable loads constrained by comfort requirements, while electrical demands include time-shiftable components representing flexible appliance usage. The bi-level optimization problem is reformulated into a tractable single-level problem using Karush-Kuhn-Tucker (KKT) conditions, with the resulting mixed-integer linear programming (MILP) formulation capturing the complex interactions between retailer pricing strategies and consumer response behaviors.

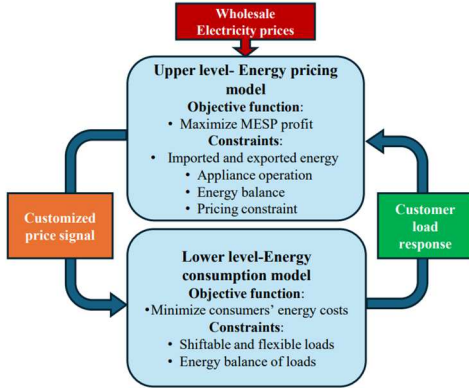


Figure 1. Model configuration

III. MATHEMATICAL FORMULATION

The proposed multi-energy trading framework incorporates a bi-level optimization problem, where the upper level maximizes the energy provider's profit through optimal operation of combined heat and power (CHP) units and gas boilers (GB), while the lower level represents the cost minimization problems of adjustable and curtailable consumers. The mathematical formulation is presented as follows.

A. Upper-level energy pricing model

The upper-level problem represents the energy provider's operation, incorporating generation units, storage systems, and network constraints. The mathematical formulation is structured as follows:

$$\text{Max } \Pi = \sum_{t=1}^T (\rho_t^e \cdot P_t^d + \rho_t^h \cdot H_t^d) - (\lambda_t^e \cdot P_t^{ex} + \lambda_t^{ng} \cdot F_t^{ng}) \quad (1)$$

$$\rho_t^{e,min} \leq \rho_t^e \leq \rho_t^{e,max} \quad (2)$$

$$\sum_{t=1}^T \frac{\rho_t^e}{T} \leq \rho_{av}^e \quad (3)$$

$$\rho_{av}^e = \sum_{t=1}^T \frac{\lambda_t^e}{T} \quad (4)$$

$$\rho_t^{h,min} \leq \rho_t^h \leq \rho_t^{h,max} \quad (5)$$

$$\sum_{t=1}^T \frac{\rho_t^h}{T} \leq \rho_{av}^h \quad (6)$$

$$\rho_{av}^h = \rho_{av}^e / 1.5 \quad (7)$$

$$F_t^{gt} = \frac{P_t^{gt}}{\eta_e^{gt} \cdot \gamma_h} \quad (8)$$

$$F_t^{gb} = \frac{H_t^{gb}}{\eta_h^{gb} \cdot \gamma_h} \quad (9)$$

$$F_t^{ng} = F_t^{gt} + F_t^{gb} \quad (10)$$

$$H_t^{gt} = \frac{P_t^{gt}}{\eta_e^{gt}} (1 - \eta_e^{gt} - \eta_e^{loss}) \eta^{hr} \quad (11)$$

$$P_{min}^{gt} \leq P_t^{gt} \leq P_{max}^{gt} \quad (12)$$

$$H_{min}^{gt} \leq H_t^{gt} \leq H_{max}^{gt} \quad (13)$$

$$H_{min}^{gb} \leq H_t^{gb} \leq H_{max}^{gb} \quad (14)$$

$$E_t^{tes} = (1 - \delta_{loss}^{tes}) E_{t-1}^{tes} + (H_t^{tes,ch} \cdot \eta_h^{tes,ch} - \frac{H_t^{tes,dch}}{\eta_h^{tes,dch}}) \quad (15)$$

$$H_{min}^{tes,ch} \cdot \vartheta_t^{tes,ch} \leq H_t^{tes,ch} \leq H_{max}^{tes,ch} \cdot \vartheta_t^{tes,ch} \quad (16)$$

$$H_{min}^{tes,dch} \cdot \vartheta_t^{tes,dch} \leq H_t^{tes,dch} \leq H_{max}^{tes,dch} \cdot \vartheta_t^{tes,dch} \quad (17)$$

$$E_{min}^{tes} \leq E_t^{tes} \leq E_{max}^{tes} \quad (18)$$

$$\vartheta_t^{tes,ch} + \vartheta_t^{tes,dch} \leq 1 \quad (19)$$

$$C_t^{ex} = \lambda_t^e \cdot P_t^{ex} \quad (20)$$

$$P_{min}^{ex} \leq P_t^{ex} \leq P_{max}^{ex} \quad (21)$$

$$P_t^{gt} + P_t^{ex} = P_t^d \quad (22)$$

$$H_t^{gt} + H_t^{gb} + H_t^{tes,dch} = \frac{H_t^d}{\eta_{he}^d} + H_t^{tes,dch} \quad (23)$$

The model formulation begins with the upper-level objective function (1), which represents the operational cost of the multi-energy provider, accounting for both procurement costs and revenue from energy sales. The offered electricity and heat prices are shown with ρ_t^e and ρ_t^h where P_t^d and H_t^d are variable demands. Wholesale electricity and gas prices are illustrated by λ_t^e and λ_t^{ng} where P_t^{ex} and F_t^{ng} are exchange electricity and purchased natural gas. Price boundaries for heating and electricity are established through constraints (2)-(7). The operational characteristics and technical constraints of generation units are modeled in equations (8)-(14), which include the Gas turbine (GT) and GB specifications. The GT power and heat are shown with P_t^{gt} and H_t^{gt} where η_e^{gt} and η_e^{loss} are power efficiency energy loss of GT and η^{hr} shows heat recovery efficiency. The GB output heat and efficiency is shown by H_t^{gb} and η_h^{gb} where γ_h shows heat value. Thermal energy storage (TES) dynamics and limitations are captured in equations (15)-(19). The current energy of TES is shown by E_t^{tes} where $H_t^{tes,ch}$ and $H_t^{tes,dch}$ are charging and discharging heat with $\eta_h^{tes,ch}$ and $\eta_h^{tes,dch}$ as efficiencies. The loss of energy coefficient in each cycle is shown by δ_{loss}^{tes} . Binary variables $\vartheta_t^{tes,ch}$ and $\vartheta_t^{tes,dch}$ enforce charging and discharging does not happen simultaneously. The power exchange with the upstream grid is bounded by constraints (20)-(21), as C_t^{ex} shows cost of exchange power while equations (22)-(23) ensure power and heat balance across the system.

B. Lower-level energy consumption model

The lower-level problem captures the consumers' behavior through two separate optimization problems for adjustable and curtailable loads. The constraints and objectives are formulated as:

$$\text{Min } \Delta = \sum_{t=1}^T (\rho_t^e \cdot P_t^d + \rho_t^h \cdot H_t^d) + [\rho_t^{e,pen} \cdot (P_t^d - P_t^{base})^2 + \rho_t^{h,pen} \cdot (H_t^{base} - H_t^d)^2] \quad (24)$$

$$P_t^d = P_t^{base} + \Delta P_t : \theta_t^{pd} \quad (25)$$

$$\sum_{t=1}^T \Delta P_t = 0 : \phi^{sh} \quad (26)$$

$$-\alpha \cdot P_t^{base} \leq \Delta P_t \leq \alpha \cdot P_t^{base} : \psi_t^{sh,min}, \psi_t^{sh,max} \quad (27)$$

$$H_t^d = H_t^{base} \cdot (1 - \beta_t^{ad}) : \theta_t^{hd} \quad (28)$$

$$0 \leq \beta_t^{ad} \leq \varepsilon : \omega_t^{ad,min}, \omega_t^{ad,max} \quad (29)$$

The lower-level problem is formulated through equation (24), which defines the operation cost for both shiftable and curtailable energy consumption patterns and discomfort function as quadratic form with $\rho_t^{e,pen}$ and $\rho_t^{h,pen}$ as penalty factors for consumers' discomfort. The dual variables are designated for each constrains- where θ_t^{pd} , ϕ^{sh} and θ_t^{hd} are considered free dual variables for equality constraints and $\psi_t^{sh,min}$, $\psi_t^{sh,max}$, $\omega_t^{ad,min}$ and $\omega_t^{ad,max}$ are correspondent positive dual variables for inequality constraints. The behavior and constraints of time-shiftable consumers are represented in equations (25)-(27), capturing their temporal flexibility. Energy adjustable consumers' characteristics and limitations are modeled through equations (28)-(29), which define their consumption boundaries and adjustment capabilities.

To transform the bi-level optimization problem into a tractable form, the model employs the Special Order Sets of Type 1 (SOS1), which linearize complementary conditions $0 \leq x \perp y \geq 0$ with KKT conditions [20]. The resulting single-level optimization problem maintains the upper-level objective function of maximizing the multi-energy provider's profit. The transformed model incorporates the original upper and lower-level constraints, supplemented by KKT optimality conditions including stationary and complementary along with primal and dual feasibility and linearized complementarity constraints. The final reformulation is as follows:

$$\frac{\partial \mathcal{L}}{\partial P_t^d} = \rho_t^e + \theta_t^{pd} + 2\rho_t^{e,pen} \cdot (P_t^d - P_t^{base}) = 0 \quad (30)$$

$$\frac{\partial \mathcal{L}}{\partial H_t^d} = \rho_t^h + \theta_t^{hd} - 2\rho_t^{h,pen} \cdot (H_t^{base} - H_t^d) = 0 \quad (31)$$

$$\frac{\partial \mathcal{L}}{\partial \Delta P_t} = -\theta_t^{pd} + \phi^{sh} + \psi_t^{sh,max} - \psi_t^{sh,min} = 0 \quad (32)$$

$$\frac{\partial \mathcal{L}}{\partial \beta_t^{ad}} = \theta_t^{hd} H_t^{base} + \omega_t^{ad,max} - \omega_t^{ad,min} = 0 \quad (33)$$

$$P_t^d = P_t^{base} + \Delta P_t \quad (34)$$

$$\sum_{t=1}^T \Delta P_t = 0 \quad (35)$$

$$H_t^d = H_t^{base} \cdot (1 - \beta_t^{ad}) \quad (36)$$

$$\Delta P_t + \alpha \cdot P_t^{base} \geq 0 \quad (37)$$

$$\psi_t^{sh,min} \geq 0 \quad (38)$$

$$\frac{(\Delta P_t + \alpha \cdot P_t^{base}) - \psi_t^{sh,min}}{2} = V1_t^+ - V1_t^- \quad (39)$$

$$\frac{(\Delta P_t + \alpha \cdot P_t^{base}) + \psi_t^{sh,min}}{2} = V1_t^+ + V1_t^- \quad (40)$$

$$\alpha \cdot P_t^{base} - \Delta P_t \geq 0 \quad (41)$$

$$\psi_t^{sh,max} \geq 0 \quad (42)$$

$$\frac{(\alpha \cdot P_t^{base} - \Delta P_t) - \psi_t^{sh,max}}{2} = V2_t^+ - V2_t^- \quad (43)$$

$$\frac{(\alpha \cdot P_t^{base} - \Delta P_t) + \psi_t^{sh,max}}{2} = V2_t^+ + V2_t^- \quad (44)$$

$$\beta_t^{ad} \geq 0 \quad (45)$$

$$\omega_t^{ad,min} \geq 0 \quad (46)$$

$$\frac{\beta_t^{ad} - \omega_t^{ad,min}}{2} = V3_t^+ - V3_t^- \quad (47)$$

$$\frac{\beta_t^{ad} + \omega_t^{ad,min}}{2} = V3_t^+ + V3_t^- \quad (48)$$

$$\varepsilon - \beta_t^{ad} \geq 0 \quad (49)$$

$$\omega_t^{ad,max} \geq 0 \quad (50)$$

$$\frac{(\varepsilon - \beta_t^{ad}) - \omega_t^{ad,max}}{2} = V3_t^+ - V3_t^- \quad (44)$$

$$\frac{(\varepsilon - \beta_t^{ad}) + \omega_t^{ad,max}}{2} = V3_t^+ + V3_t^- \quad (44)$$

$$W_t^d \geq \rho_t^{e,min} \cdot P_t^d + \rho_t^e \cdot P_t^{d,min} - \rho_t^{e,min} \cdot P_t^{d,min} \quad (54)$$

$$W_t^d \geq \rho_t^{e,max} \cdot P_t^d + \rho_t^e \cdot P_t^{d,max} - \rho_t^{e,max} \cdot P_t^{d,max} \quad (55)$$

$$W_t^d \leq \rho_t^{e,max} \cdot P_t^d + \rho_t^e \cdot P_t^{d,min} - \rho_t^{e,max} \cdot P_t^{d,min} \quad (56)$$

$$W_t^d \leq \rho_t^e \cdot P_t^{d,max} + \rho_t^{e,min} \cdot P_t^d - \rho_t^{e,min} \cdot P_t^{d,max} \quad (57)$$

$$W_t^d \geq \rho_t^{e,min} \cdot P_t^d + \rho_t^e \cdot P_t^{d,min} - \rho_t^{e,min} \cdot P_t^{d,min} \quad (58)$$

$$W_t^d \geq \rho_t^{e,max} \cdot P_t^d + \rho_t^e \cdot P_t^{d,max} - \rho_t^{e,max} \cdot P_t^{d,max} \quad (59)$$

$$W_t^d \leq \rho_t^{e,max} \cdot P_t^d + \rho_t^e \cdot P_t^{d,min} - \rho_t^{e,max} \cdot P_t^{d,min} \quad (60)$$

$$W_t^d \leq \rho_t^e \cdot P_t^{d,max} + \rho_t^{e,min} \cdot P_t^d - \rho_t^{e,min} \cdot P_t^{d,max} \quad (61)$$

The nonconvex bilinear term in upper level is linearized using McCormick envelope by replacing $W_t^d = \rho_t^e \cdot P_t^d$ and $W_t^h = \rho_t^h \cdot H_t^d$ and converted to (54)-(61). This reformulation (30)-(61) along with (2)-(23) yields the MILP single-level optimization problem that can be solved using MILP solver CPLEX.

IV. SIMULATION RESULTS

A. Input data

The proposed MESP model comprises of one CHP unit with maximum 1500 kW power, one gas boiler with 4000 kW and TES where the whole data regarding the parameters and efficiencies can be concluded from [21]. The proposed model is implemented in a residential building housing 500 occupants, alongside a large office space. The dataset used for this study originates from New York City, ensuring relevance to urban energy consumption patterns [22]. The input data considers a typical day in winter in January. The input data for electricity prices is sourced from [23], while natural gas price data is obtained from [24]. The input data regarding demands is from a typical day in winter in January shown in Figure. 2.

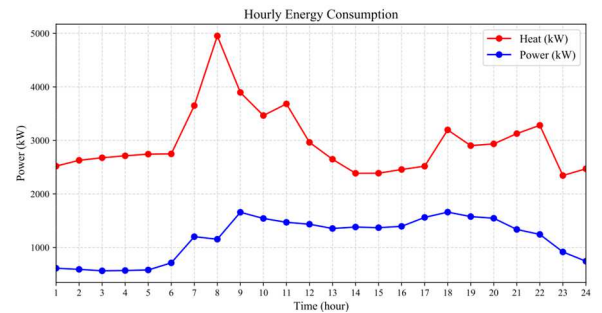


Figure. 2. Hourly energy consumption

B. Results

The proposed model aims to optimize a bi-level optimization problem where upper level maximizes the profit and the lower level minimizes its costs while maintaining comfort level of consumers. The impact of demand response on profit and the cost of MESP is analyzed and the bi-level pricing model is compared to single level without demand response. The discomfort level efficiency (penalty price) is 0.00043 and 0.00086 for electricity and heat as conservative high comfort level. By reducing and increasing this factor, the DR impact will be changed. The results show that the MESP has the profit of \$2374.4. The cost of MESP in case of single level without DR is \$3720.1 while in case of bi-level DR with full participation in DR the energy cost is \$3169 (almost zero penalty for comfort level), which is 14.8% less. When considering the medium comfort level (10% of penalty), the energy costs for MESP will be \$3306 and with higher comfort level penalty, the energy costs will be \$3573 (90% of penalty). The energy costs for customer on the other hand will be \$2409, \$2480 and \$2591 when setting discomfort penalty price from high to low, respectively indicating not participating in DR will increase the energy costs as consequence of consuming more energy. Figure. 3 shows the electricity market that compared to Offered heat and electricity prices. The MESP buys electricity and gas and then gives different offered prices to customer. The price for heat is higher in periods where heating demand is higher such as 06:00-10:00 and lower in periods when heat demand is low such as 13:00-17:00. For offered electricity price the similar approach can be concluded. Figure. 4 illustrates the impact of shiftable and adjustable loads on demands. The heat demand is decreased in almost all the periods and curtailed more in peak such as 08:00 and less in off peak such as 15:00. The shifted electricity mostly follows the electricity price combined with natural gas price fluctuation, given that gas turbine is the primary supply for electricity.

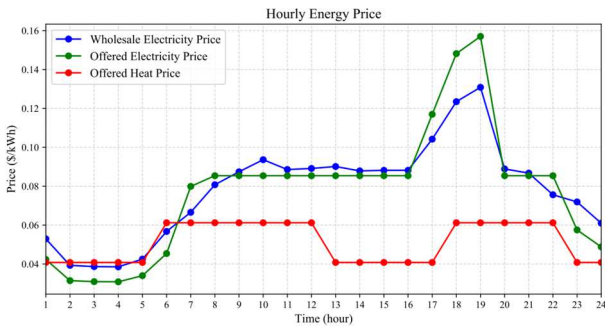


Figure. 3. Hourly energy price

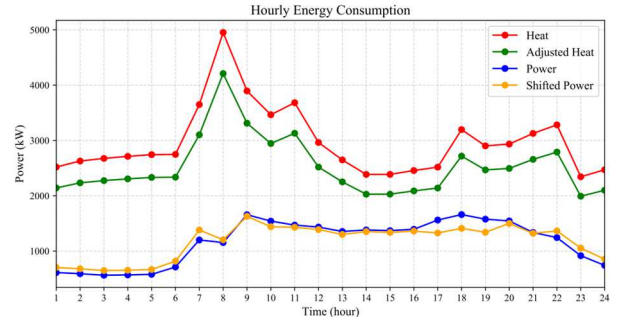


Figure. 4. DR impact on energy consumption

MESP power and heat transactions are also considered for analysis of the proposed optimization. For power transactions, Figs. 5-6 show illustrates most of the power provided for the customer is from gas turbine and grid in some instances where the power demand was higher than the capacity of the gas turbine such as 09:00 and 18:00 for single level problem without demand response. When using DR in bi-level approach, the electricity is shifted in some periods such as 17:00-19:00. Also, the electricity is sold to the grid in case of excess of energy when electricity price is high at 17:00-19:00 in DR mode.

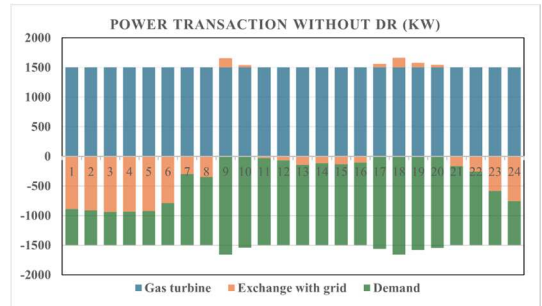


Figure. 5. Power transaction of MES

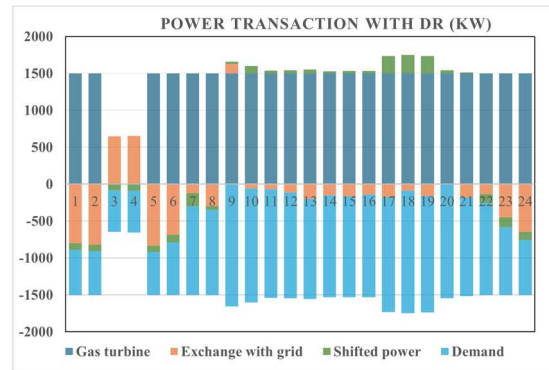


Figure. 6. Power transaction of MES with DR

The heat transaction is shown in Figs. 7-8. Most of the supplied heat is coming from gas turbine and gas boiler. It should be noted that the heat demand is considered after heat exchanger unite with efficiency of 0.9 in the demand and supply of heat. As shown in case without DR, the TES is working in some hours by

charging and discharging to compensate for energy deficiency and increase flexibility. For instance, in high heat demand hours such as 07:00-10:00 the TES starts discharging the energy stored at 02:00-05:00. In contrast, in case of adjusted heat demand with DR, the TES is not active, and the flexibility is applied using DR and most of the hours the heat demand is adjusted and curtailed to some extent to make the system flexible.

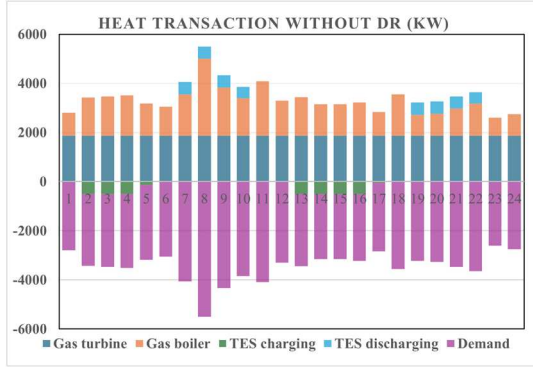


Figure 7. Heat transaction of MES

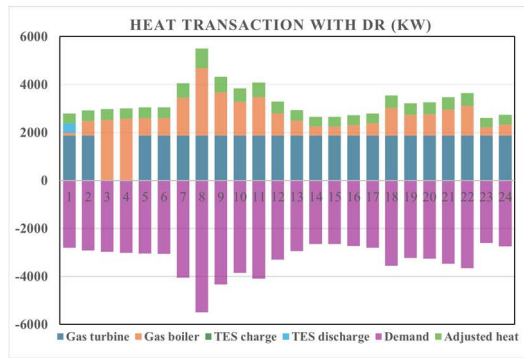


Figure 8. Power transaction of MES with DR

V. CONCLUSION

This study presents a bi-level optimization framework for MESP to enhance energy efficiency, reduce operational costs, and support DR strategies in urban energy systems. By integrating electricity and heating demands within a coordinated MES framework, the model enables dynamic pricing and flexible load management, fostering a symbiotic relationship between the MESP and consumers. The results demonstrate that the bi-level approach significantly outperforms single-level optimization, reducing the MESP's energy costs by 14.8% and natural gas costs by 12.8%. Consumers benefit from adjusted heating, shifting loads to off-peak periods and curtailing demand during high-price intervals, which lowers their expenses. By leveraging DR, the system reduces peak demand, enhances flexibility, and optimizes resource allocation through gas turbines, grid interactions, and TES. Notably, the model eliminates reliance on TES during DR operation, instead relying on demand curtailment and load shifting to maintain balance.

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