Two-Stage Approach for Demand Side Management in Multi-Smart Grids

Muhammad Bilal Khan and Tahir Mehmood

Electrical Engineering Department, University of Engineering and Technology Taxila, 47070, Pakistan Corresponding author: Tahir Mehmood (Email: tahir.mehmood@uettaxila.edu.pk

*Abstract***— In the face of escalating electricity demand driven by technological advancements and a growing population, efficient management becomes imperative. This study explores demand-side management (DSM) within smart grids (SGs) to minimize customer bills, alleviate peak loads, and mitigate losses. The research employs diverse strategies and compares their effectiveness, focusing on optimal load consumption across smart microgrids. Key contributions include a DSM strategy for cost reduction, efficient peak load reduction, and active power loss minimization in smart microgrids. The proposed approach is validated through simulations, with results contributing to real-world SG implementation. The study highlights a 23.4% and 31.6% cost saving for residential and commercial customers, respectively, and emphasizes the significance of load management in enhancing operational efficiency and cost-effectiveness within the energy hub framework. The research provides valuable insights for developing advanced consumption management strategies, ensuring energy efficiency and sustainability in future power systems.**

*Index Terms***—** *Optimization of Hub, Distributed Generation, Energy Hub and Smart Grid*

I. INTRODUCTION

N an era where technological advancements and an ever-IN an era where technological advancements and an ever-
Lexpanding population drive an insatiable demand for electricity, the challenges of efficiently managing this surge in consumption are more pronounced than ever. During peak hours, meeting this escalating demand poses formidable hurdles, aggravated by environmental, technical, and economic constraints. In response to this, demand response programs integrated into a smart grid (SG) infrastructure emerge as critical solutions. This study delves into the effective management of shiftable loads within various microgrids under the SG framework, with a primary objective of minimizing customer bills, alleviating peak loads, and mitigating losses. The research employs diverse strategies, subjecting them to a comparative analysis to ascertain their effectiveness in achieving these vital objectives [1-6].

The central problem this research addresses revolves around devising an optimal strategy for demand-side management within smart grids (SGs) using a robust approach. As countries experience economic growth heavily reliant on energy and power, the thirst for electricity intensifies. Expanding power stations and transmission lines appears to be an inevitable solution; however, the construction of new facilities comes at a significant cost and carries a heavy environmental footprint. In a bid to navigate these challenges and attain optimal energy consumption while curbing demand growth, leveraging Demand-Side Management (DSM) programs and integrating renewable resources into microgrids is proposed [5, 7-10]. DSM encompasses key steps such as load management, energy efficiency, and energy savings. The Demand Response program, a prominent facet of DSM, empowers consumers across commercial, residential, and industrial sectors to optimize their electricity consumption patterns, thereby reducing billing costs and enhancing system reliability. The introduction of Smart Grids (SGs) provides customers the flexibility to adjust their consumption patterns in line with network needs and priorities, incorporating interconnected elements with telecommunications links [11-16]. The management infrastructure within SGs plays a pivotal role in facilitating seamless electricity and information flow, thereby bolstering the efficacy of management strategies. Given the significance of DSM programs and the pivotal role played by SG infrastructure in efficient load management, this research is meticulously designed to craft a robust approach for demandside management in SGs [7, 17-24].

The vast amount of information available in SGs has necessitated the adoption of multi-agent systems (MAS) as an effective method for managing such large systems. Intelligent agents representing various loads in the power system follow unified strategies to achieve specific goals, such as setting optimal temperatures for residential buildings, reducing peak load, minimizing energy consumption, and cutting down consumer electricity costs [25].

Furthermore, blockchain technology has gained popularity in SGs to optimize energy consumption and regulate lighting, heating, and overall energy usage while reducing Peak-to-Average Ratio (PAR) and energy consumption [17].

- The following are the key contributions of the research:
- The research focused on promoting a DSM strategy

that effectively reduces the cost of billing for consumers in smart microgrids.

- The research implemented a demand-side management program that can efficiently reduce peak loads and flatten the load lines.
- The research optimized the DSM approach to minimize active energy losses.

II. LITERATURE REVIEW

In the initial study [2], researchers investigated load curve adjustment through peak-shaving and load-shifting techniques, primarily targeting the reduction of peak demand and customer billing costs. Additionally, the study examined the loads of educational facilities for Demand-Side Management (DSM), characterized by relatively consistent load fluctuations. In a separate investigation [3], flywheel technology was employed to address losses and prevent overloads in power grid transformers during peak periods. The study implemented a two-tier hierarchical strategy, employing a predictive controller at the first level to address the objective function and real-time measurements at the second level to rectify initial inaccuracies. Hybrid methods have been introduced in several studies [3–5]. In certain literature, researchers have proposed approaches based on Multi-Agent Systems (MAS) or Artificial Intelligence (AI) methods, focusing on load shift management in various residential, commercial, and industrial areas to reduce electricity bills for consumers [7-9].

Within the domain [8–11], research has focused on investigating microgrids that include electric vehicles, solar panels, energy storage systems, local loads, and intelligent measurement systems. Concepts such as Vehicle-to-Building (V2B) and Vehicle-to-Grid (V2G) were utilized to enable power exchange with microgrids, aiming to reduce unwanted peak loads, enhance electric vehicle power supply, and increase the utilization of solar panels. However, these studies predominantly focus on solar panel power consumption during peak times, without considering the diverse loads present in a real network [5,6].

*T*he objective of the research was to minimize active power loss and provide voltage regulation while achieving load peak shaving and reducing the traveling cost of mobile energy storage systems.

Moreover, some studies have focused on managing specific loads, such as electric water heaters, through dynamic programming [15-17]

A pressing issue in SGs is the increasing penetration of solar panels, which can adversely affect the network load curve, causing the "duck curve" phenomenon. A consumption management system proposed in a study [18] that provides better optimization for water heaters, ACs, Air heating systems, and batteries.

The advancements in Artificial Intelligence (AI) and deep learning methods, alongside technologies like IoT and the big data, have enabled the collection and storage of instantaneous network load consumption data. AI methods incorporating machine learning have been utilized to predict load response patterns, providing valuable insights for consumption management [19–21]. However, these references have primarily focused on analyzing consumption information from some consumers and addressing consumer privacy protection. Recent research has explored [22–24], for example, a study [26] presents a organization approach to energy exchange, efficiently reducing the interior top load of insolent homes by vending extra power to other homes during definite hours and simultaneously reducing the overall network peak level.

The increasing electricity demand driven by technological advancements and population growth poses challenges in meeting peak-hour requirements. This study focuses on demand response programs within the smart grid infrastructure, specifically managing shiftable loads in residential, commercial, and industrial microgrids. The approach of load shifting is framed as a multi-objective optimization challenge aimed at diminishing customer bills, minimizing peak loads and losses, and enhancing network voltage. Simulations using the Simplex algorithm in GAMS and the Improved Grey Wolf Optimization in MATLAB compare the proposed program's effects, with the CPLEX solver demonstrating superior outcomes in peak load reduction (6.7%, 1%, and 16% in residential, commercial, and industrial microgrids, respectively) and production cost reduction (over 3.5%, 2.2%, and 3.9%, respectively). These findings emphasize the importance of advanced optimization algorithms for efficient DSM and cost savings in the evolving smart grid landscape [1]. In conclusion, the literature review encompasses a diverse range of studies focusing on consumption management in SGs. Researchers have explored various methods, including hybrid approaches, stochastic and statistical models, AI techniques, multi-agent systems, and blockchain technology, to optimize demand-side management strategies, address peak load challenges, reduce costs, enhance energy efficiency, and mitigate environmental impacts. The research area is interdisciplinary, encompassing AI, deep learning, IoT, big data, and blockchain technologies, all aimed at enhancing the efficiency, sustainability, and reliability of DSM strategies in Smart Grids.

III. METHODOLOGY

The energy hub problem employs a domestic and industrial model, incorporating components such as CHP, chillers, EHP, boilers, PV, and electric heaters. The objective is to determine the capacities of these hub assets in a manner that minimizes total power losses and operating costs.

The impartial purpose of the difficulties consists of three terms, FDSM, F-Loss and factors. To achieve a multi-objective optimization, weight coefficients (k1, k2, and k3) are introduced, each ranging between 0 and 1.

Figure 1 The analyzed Energy Hub Model

These weight coefficients represent the relative importance of each objective in the optimization process, and their sum equals 1, ensuring that all objectives are appropriately balanced.

The objective function can be represented as follows:

Objective Function

$$
= Min (k1 * FDSM + k2 \n * FLoss) \tag{1}
$$

Where:

k1, k2, and k3 are the weight coefficients for the respective terms $(0 \le k1, k2 \le 1)$

FDSM represents the demand-side management function, aiming to optimize the load shift and achieve peak load reduction, cost reduction, and improved energy efficiency.

FLoss represents the objective of minimizing active power loss in the power distribution network, contributing to energy conservation and network efficiency.

By assigning appropriate weight coefficients to each term, the optimization process can be tailored to address specific priorities and preferences in the smart grid's demand-side management while considering the trade-offs between different objectives.

$$
Pv(t) = Npv * SS * I * (1 - 0.005 * tout - 25)
$$
\n(2)
\nThe solar irradiance is employed to assess the output of the P

The solar irradiance is employed to assess the output of the PV in the equation mentioned above. Operational cost of Chiller, Boiler are stated below: [25]

$$
OC_Boiler(t) = data(t, 'Lamd_gas') * (((H_Boiler(t) * DEL_T)/EFF_Boiler); (3)
$$

$$
OC_Chiller(t) = a_Chiller * (C_Chiller(t) * DEL_T) + b_Chiller (4)
$$

The demand-side management function (FDSM) within the objective function strives to reduce the difference between the ideal load curve (ILC) and the optimized load curve (OLC) following the implementation of the consumption management program. This objective is mathematically expressed through equation (5).

 $FDSM = \Sigma N (OLC(t) - ILC(t))^2$ (5)

Here, N represents the total number of time intervals considered for optimization. ILC(t) represents the ideal load curve at time t, while OLC(t) denotes the optimized load curve obtained when the consumption management program is applied starting at time t. The OLC at time t can be expressed using equation (6) $OLC(t) = EL(t) + ONSL(t) - OFFSL(t)$ (6)

Where: EL(t) - Estimated load at time t, ONSL(t) - Net impact of ON shiftable loads at time t and OFFSL(t) - Net impact of OFF shiftable loads at time t.

The calculation of ONSL(t) involves considering two terms: the shiftable loads that move from times before t to t and impact the load at time t (first term), and the loads available after period t that moved from their later consumption periods (CP) and impact the load at time t (second term). The equation (7) represents the expression for ONSL(t) [25].

 $ONSL(t) = \sum \sum \sum$ Zwnt. $PL1w + \sum \sum \sum$ Zwnt - 1. $PL(1 +$ f)w (7)

By formulating FDSM and its corresponding equations, the optimization process aims to align the actual load curve with the desired ideal load curve after implementing the consumption management program, effectively managing the peak loads and enhancing the performance of the smart grid

A. *IMPROVED GREY WOLF OPTIMIZATION (IGWO) ALGORITHM:*

The Improved Grey Wolf Optimization (IGWO) algorithm is a nature-inspired optimization method derived from the social structure and hunting behavior observed in grey wolves. This algorithm builds upon the original Grey Wolf Optimization (GWO) and introduces enhancements to improve its efficiency and convergence speed [25].

At the core of the IGWO algorithm are three main types of wolves: alpha, beta, and delta wolves. These wolves represent the best solutions found so far in the optimization process. Additionally, the IGWO algorithm introduces two more types of wolves, namely sigma and omega wolves, to further diversify the search space and enhance exploration.

The FLoss component of the objective function is focused on minimizing active power loss in the power system after the implementation of the consumption management program. The objective is expressed using the equation (8):

$$
FLoss = \Sigma N \Sigma Nb (Rb \times I^2 \times tb)
$$
 (8)

Here, N represents the total number of time intervals considered for optimization, and Nb represents the total number of network branches in the power system. The objective function aims to optimize the values of current (Itb) flowing through each branch (b) at time t, and Rb represents the resistance of the bth branch. The IGWO algorithm also introduces a parameter called the grey wolf index (GWI), which influences the step size and direction of each wolf's movement during the optimization process. By adjusting the GWI, the algorithm can strike a balance between exploration and exploitation, allowing it to efficiently navigate the solution space.

As the optimization process continues, the IGWO algorithm iteratively refines the positions of the wolves, aiming to converge towards the optimal solution. The algorithm terminates once a stopping criterion is achieved in the given condition set [23].

In the context of the research on consumption management in the smart grid, the IGWO algorithm is employed to optimize losses in the power distribution network. By applying IGWO, the researchers aim to identify the optimal distribution of power within the grid, minimizing active power losses and enhancing energy efficiency. This optimization process contributes to the overall objective of reducing energy costs and improving the performance of the smart grid.

IV. RESULTS AND DISCUSSION

The proposed research primarily seeks to optimize load consumption across diverse buildings within a multi smart grid environment, all while addressing paramount objectives such as reducing customer bills, mitigating peak loads, and minimizing losses. Through rigorous simulations, performance evaluations, and comprehensive comparison studies, this research endeavors to validate the effectiveness and efficiency of the developed demand-side management strategy for multi smart grids using

robust optimization algorithms [15]. The results derived from this validation process will serve as a compass, offering crucial insights for practical implementation and continual enhancements of the DSM strategy within real-world smart grid environments.

Asset	TOC
CHP	1103
Boiler	85.5
Chiller	0.91
EHP	6.562
Heater	θ
TOC	2243.625

 Table 1 The Energy Hub Model Results for Residential Customers

The results helped in determining optimal values for components within an energy hub, such as CHP, Boiler, EES, Chiller, EHP, and Heater. The reduced operational costs are derived from equations incorporating constraints and are stated in Table 1.

Area	Customer Bill (\$)	Active Power Loss (KW)		
	Without DSM With DSM		Cost Reduction	
Residential	1974	1950.6	23.4	110.4
Commercial . <i>. .</i>	3734	3702.4 .	31.6	215.6 .

Table 2 Customer bills and Active power losses result table

The outcomes of research have proven instrumental in mitigating both customer bills and active power losses for a diverse range of consumers, including residential and commercial sectors (Table 2). Through the implementation of our findings, significant reductions in financial burdens for customers have been achieved, concurrently with a notable decrease in active power losses. This not only underscores the practical effectiveness of our approach but also highlights its potential for widespread applicability across various consumer segments, contributing to enhanced economic and operational efficiencies.

Figure 2(a) Load Profiles before and after for (a) Residential load and (b) Commercial load

The findings illustrate that optimal performance of an energy hub is achievable through the implementation of demand-side management (DSM) strategies. Skillful handling of load management proves instrumental in realizing cost savings for customers, particularly through the effective peak shaving of adjustable loads. The adoption of DSM methodologies is justified, given that only a modest 3% of the total load can be feasibly shifted from peak to off-peak hours.

The expected outcome of this research is to develop an efficient and effective consumption management program for smart grids (SGs) that can effectively optimize the load curve, reduce peak demand, and minimize operational costs while ensuring network stability and reliability.

V. CONCLUSION

The implementation off demand response programs and utilizing the IGWO algorithm, the research aimed to achieve a substantial reduction in peak load during critical hours. This reduction in peak demand will help alleviate stress on the power system, improve network stability, and avoid overloading during peak periods. The research highlights the significance of strategic load management in enhancing overall operational efficiency and cost-effectiveness within the energy hub framework.

Results indicated the cost saving of 23.4% and 31.6% while the active power losses are 110.4 and 215.6 kw for residential and commercial customers respectively. Total operational cost is 2243.625 dollars for the proposed model indicating the success of adopted model.

In this research, In the future, the research will contribute valuable insights into the development of advanced consumption management strategies for smart grids. The findings will have practical applications in real-world power systems, promoting energy efficiency, cost-effectiveness, and sustainability in the face of increasing electricity consumption and demand.

REFERENCES

- [1] Ebrahimi, J., & Abedini, M. (2022). A two-stage framework for demandside management and energy savings of various buildings in multi smart grid using robust optimization algorithms. Journal of Building Engineering, 53, 104486.
- [2] T.J. Wilbanks, S. Fernandez, Climate Change and Infrastructure, Urban Systems, and Vulnerabilities: Technical Report for the US Department of Energy in Support of the National Climate Assessment, Island Press, 2014. .
- [3] P. Bhat Nempu, N.S. Jayalakshmi, Coordinated power management of the subgrids in a hybrid AC–DC microgrid with multiple renewable sources, IETE J. Res. 26 (2020) 1–11.
- [4] D. Mariano-Hern´andez, et al., A review of strategies for building energy management system: model predictive control, demand side management, optimization, and fault detect & diagnosis, J. Build. Eng. 33 (2021).
- [5] David Rib´o-P´erez, et al., A critical review of demand response products as resource for ancillary services: international experience and policy recommendations, Energies 14 (4) (2021) 846.
- [6] Amam Hossain Bagdadee, Li Zhang, A review of the smart grid concept for electrical power system, Res. Anthol. Smart Grid Microgrid Dev. (2022) 1361–1385. .
- [7] R. Dharani, et al., Load shifting and peak clipping for reducing energy consumption in an Indian university campus, Energies 14 (3) (2021) 558. .
- [8] L. Tziovani, et al., Energy management and control of a flywheel storage system for peak shaving applications, IEEE Trans. Smart Grid 12 (5) (2021) 4195–4207.
- K. Jinseok, K.I. Kim, Data-driven hybrid model and operating algorithm to shave peak demand costs of building electricity, Energy Build. 229 (2020).
- [10] R. Md Masud, et al., A novel peak load shaving algorithm for isolated microgrid using hybrid PV-BESS system, Energy (2021) 234.
- [11] Banala Venkatesh, et al., Managing the demand in a micro grid based on load shifting with controllable devices using hybrid WFS2ACSO technique, Energies 15 (3) (2022) 790.
- [12] Ruud Egging-Bratseth, et al., Seasonal storage and demand side management in district heating systems with demand uncertainty, Appl. Energy 285 (2021).
- [13] P. Scarabaggio, S. Grammatico, R. Carli, M. Dotoli, Distributed demand side management with stochastic wind power forecasting, IEEE Trans. Control Syst. Technol. 30 (1) (2021) 97–112.
- [14] T. Logenthiran, D. Srinivasan, T.Z. Shun, Multi-agent system for demand side management in smart grid, in: IEEE Ninth International Conference on Power Electronics and Drive Systems, 2011, pp. 424–429.
- [15] T. Logenthiran, D. Srinivasan, T.Z. Shun, Demand side management in smart grid using heuristic optimization, IEEE Trans. Smart Grid 2 (3) (2012) 1244–1252.
- [16] V. Mukherjee, Day-ahead demand side management using symbiotic organisms search algorithm, IET Gener., Transm. Distrib. 12 (14) (2018) 3487–3494.
- [17] J. Ebrahimi, M. Abedini, M.M. Rezaei, Optimal scheduling of distributed generations in microgrids for reducing system peak load based on load shifting, Sustain Energy Grids Network 23 (2020), 100368.
- [18] Yanchong Zheng, Ziyun Shao, Linni Jian, The peak load shaving assessment of developing a user-oriented vehicle-to-grid scheme with multiple operation modes: the case study of Shenzhen, China, Sustain. Cities Soc. 67 (2021), 102744. .
- [19] Ahmed Ouammi, Peak load reduction with a solar PV-based smart microgrid and vehicle-to-building (V2B) concept, Sustain. Energy Technol. Assessments 44 (2021), 101027. .
- [20] Rana, Md Masud, et al., A novel peak load shaving algorithm for isolated microgrid using hybrid PV-BESS system, Energy 234 (2021), 121157. .
- [21] Y. Guo, Z. Qianzhi, W. Zhaoyu, Cooperative peak shaving and voltage regulation in unbalanced distribution feeders, IEEE Trans. Power Syst. 36 (9) (2021) 5235–5244. .
- [22] Mohammad Reza Sheibani, et al., Modeling the energy storage systems in the power system studies, in: Synergy Development in Renewables Assisted Multi- Carrier Systems, Springer, Cham, 2022, pp. 497–517. .
- [23] Soi Jeon, Dae-Hyun Choi, Joint optimization of Volt/VAR control and mobile energy storage system scheduling in active power distribution networks under PV prediction uncertainty, Appl. Energy 310 (2022), 118488. .
- [24] Mansouri, S.A., Ahmarinejad, A., Javadi, M.S. and Catalão, J.P., 2020. Two-stage stochastic framework for energy hubs planning considering demand response programs. Energy, 206, p.118124.
- [25] Pantelis Dimitroulis, Miltiadis Alamaniotis, A fuzzy logic energy management system of on-grid electrical system for residential prosumers, Elec. Power Syst. Res. 202 (2022), 107621.