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Optimal Scheduling of Multi-carrier Energy System Considering Nudge-based Behavioral Integrated Demand Response

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ABSTRACT

Nudge theory, a concept in behavioral science, advocates for the use of reinforcement, encouragement, and subtle recommendations to encourage voluntary adherence and shape the motivations and decisions of individuals or groups. This approach has emerged as an influential method for steering consumer behavior in energy consumption, thereby optimizing energy system operations. In this regard, demand response (DR) policies in energy systems have significant potential to align with behavioral and nudge theory concepts. This paper incorporates positive real-world incentives into DR modeling for both electricity and heating systems, aiming to influence household and customer decision-making in energy consumption through behavioral concepts. Therefore, this study introduces an optimal scheduling framework for multi-carrier energy systems that incorporates nudge-based behavioral integrated demand response (NBIDR), which combines behavioral principles into a DR program (DRP) for both electricity and heating systems. The suggested mixed integer linear programming (MILP) framework was applied to the IEEE 33-bus test system. Simulation results demonstrate the effectiveness of the proposed framework by smoothing load profiles as well as decreasing operation costs and expected energy not supplied (EENS) for both electricity and heating infrastructures.

1. Introduction

In today's energy landscape, demand response programs (DRPs) play a vital and efficient role in encouraging demand-side resources to engage with renewable energy sources (RESs) within the power system. However, traditional DR approaches do not fully exploit the potential of demand-side resources, thereby limiting energy consumer participation in the electric power system. By integrating electricity, heating, natural gas, and other energy carriers, DR initiatives can actively influence various energy forms, including inelastic loads, thereby maximizing resource interaction capacity to achieve sustainable energy systems [1], [2].

Hence, over the past few years, various scientists have introduced distinct policies and creative structures for implementing DR in multi-carrier energy systems (MCESs) [3]. In this regard, Ref. [4] examines a novel optimization scheduling model designed for multi-energy microgrids, effectively coordinating integrated demand response (IDR) with the flexible operation of waste heating utilization. Ref. [5] emphasizes a decentralized energy management framework focusing on the water-energy nexus within a RESs integrated grid-connected microgrid. Ref. [6] integrates multiple energy generation and storage units along with various DR configurations, applying a two-stage distributionally robust optimization (DRO) approach. The authors in [7] present a two-stage

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framework aimed at customer-oriented scheduling for an active distribution system, incorporating a flexible IDR that includes the involvement of smart residential consumers. Ref. [8] introduces a mixed integer nonlinear programming (MINLP) framework intended for the optimal scheduling of components in a multi-energy hub (EH) system, which includes a DRP while accounting for uncertainties in wind and solar resource behavior, with goals of minimizing costs, emissions, and consumer dissatisfaction.

In Ref. [9], the authors suggest a multi-timescale optimal operation framework for integrated energy systems that takes into account the variable operating conditions of generation, conversion, and storage equipment, as well as utilizing a day-ahead and intra-day DRP to motivate active participation in demand-side management programs. Ref. [10] proposes a multi-timescale optimal operation framework for integrated energy systems that considers the varying operational conditions of generation, conversion, and storage equipment, together with a day-ahead and intra-day DRP to foster customer involvement in demand-side management initiatives. Ref. [11] evaluates the coordination of electric vehicles (EVs) with hydrogen storage systems (HSSs) and IDR to enhance flexibility, using a robust optimization (RO) method while addressing the uncertainty of electricity prices. Furthermore, Ref. [12] presents an intelligent, data-driven hierarchical energy management framework comprising four levels of objective functions aimed at optimally coordinating IDR, energy storage systems (ESSs), and RESs within a MCES.

Furthermore, Ref. [13] introduces a stochastic framework for MCESs, integrating electricity and thermal DRP while aiming at improving the load profiles and cost reduction. The authors in [14] employ electrical and thermal DRP within a two-stage multi-objective optimization framework aiming to improve the operational efficiency of MCES under the uncertainty and variability of RESs. In Ref. [15], the authors suggest a dual-sector DRP in a scenario-based model as well as probabilistic framework to realize energy demand and supply balance for the electrical and cooling loads. Ref. [16] employs a hybrid technique to integrate unified energy storage systems with plug-in electric vehicle-based DRP, aiming at reducing emissions and minimizing operation costs.

Furthermore, Ref. [17] aims to reduce the uncertainty effects (uncertainty in loads, market prices and RESs) through electrical and thermal DRP by load shifting from the peak hours to off-peak hours in MCES. Ref. [18] aims at environmental and operation costs reduction and employs DRP for electrical shiftable loads and integrated DRP through a thermodynamic model of cooling and heating loads. In addition, the authors in [19] utilize electrical and thermal DRPs to realize optimal operation of MCESs in dealing with uncertain resources. In Ref. [20], the authors suggest a novel green energy scheduling approach for MCES to minimize emissions and costs within a smart city reliant on grid-connected power. This research employs DRPs aiming to realize reliable smart city energy system through uncertainty management of RESs. Ref. [21] aims to realize optimal operation of MCES through a multi-energy (heating, electricity, cooling, hydrogen and gas) market framework as well as incorporating DRPs for different energy carriers.

The main novelty of Ref. [22] is introducing a three-level framework for optimal operation and reconfiguring and operation of MCESs in distribution systems which models residential DRP aggregator competition. Ref. [23] introduces a stochastic optimization framework involving DRP for participating in the energy market utilizing a water wave optimization (WWO) algorithm. This paper denotes that DRP implementation can be effective in improving load curve by shifting demand from peak hours to off-peak. Furthermore, Ref. [24] introduces a multi-timescale game optimization framework for MCES including multiple types of DRP utilizing improved particle swarm optimization (PSO) algorithm. Table I describes a summary of reviewed studies in implementing DRPs in MCESs.

Although some research has looked into the incorporation of DR in MCESs, the application of nudge theory and behavioral principles within these systems has been infrequently explored. Building on our previous research [25], this study combines behavioral concepts within DR programs for both electrical and heating systems, introducing the nudge-based behavioral integrated demand response (NBIDR) framework aimed at the optimal scheduling of multi-carrier energy systems. The specific contributions and advancements beyond the earlier version ([25]) are that this study models and incorporates behavioral concepts in both electrical and heating systems within an integrated demand response framework, while [25] employs and discusses behavioral economics principles only for electrical demand.

The main contributions of this paper can be outlined as follows:

- ✓ Incorporating behavioral economics concepts in both electricity and heating systems as a nudge-based behavioral integrated demand response (NBIDR) framework,
- ✓ Evaluating the proposed framework's impact on load profiles, operation cost, and energy not supplied in both electricity and heating energy systems.

2. Scheduling of MCES Considering NBIDR

2.1. Problem Statement

Nudge theory is a concept that emerged in behavioral economics, first introduced in 2008 by Richard Thaler in a book of the same name. A key aspect of this theory is its psychological foundation, which is crucial for understanding human behavior. Nudge theory incorporates elements from behavioral economics, social psychology, and political theory, advocating indirect suggestions and positive reinforcement to influence individual and group motivations and decision-making without coercion. As a result, nudge theory serves as a valuable strategy and innovative tool that complements existing approaches. It has important applications across various fields, including business, healthcare, politics, and the protection of public goods, effectively guiding people's behavior. Notably, one critical area where nudge theory can have a profound impact is in managing energy consumption [26]-[29].

This study incorporates several principles and concepts from behavioral economics that are pertinent to the decision-making process regarding the implementation of DR programs. These principles include the endowment effect (EE), status-quo bias (SQ), concern for fairness (CF), and loss aversion (LA), all of which aim to foster positive reinforcement in DR modeling and execution while seeking to sway household and customer choices toward participating in DR initiatives. This study introduces an optimal scheduling framework for multi-carrier energy systems that incorporates nudge-based behavioral integrated demand response (NBIDR), which combines behavioral principles into a DR program for both electricity and heating systems. In this context, an optimization problem is formulated from a utility standpoint, with the objective of reducing operation costs in a multi-carrier energy system while taking into account

Table I. Summary of reviewed studies in implementing DRPs in MCESs

Ref.	Problem Type	DRP Modelling	BE and Nudge Concepts Consideration	Objective Function	Solution Methodology	Main Contribution
[4]	Environment-friendly economic optimal scheduling	IDR	No	Economic	Improved particle swarm optimization (PSO)	Scheduling of MCES with storage and carbon capture whit employing waste heat utilization
[5]	Decentralized energy management	IDR	No	Economic	Alternating direction method of multipliers	Scheduling of community MCES microgrid with modeling the water-energy nexus
[6]	Distributionally robust optimization	DR	No	Emission/ Economic	Column and constraint generation (C&CG)	Scheduling of MCES considering prices uncertainties through a data driven method
[7]	Customer-oriented scheduling	IDR	No	Comfort/ Economic	Dynamic Nonlinear Programming (DNLP) And MILP	Customer-oriented scheduling of MCES involving IDR
[8]	Multi-objective optimization	DR	No	Dissatisfaction/ Economic/ Emission	Mixed-Integer Nonlinear Programming (MINLP) and the fuzzy satisfaction method	Scheduling of MCES aiming at optimizing consumer dissatisfaction, emission and cost considering uncertainty
[9]	Multi-time scale optimization	Dual demand response (DDR)	No	Economic	N/A	Study of integrated MCES involving DDR and dynamic EH
[10]	Risk-constrained stochastic scheduling	Electrical, thermal, and cooling DR	No	Economic	Slime Mold Algorithm (SMA)	Stochastic scheduling of MCES that constrained by risk, utilizing the Conditional Value at Risk (CVaR) approach
[11]	Day-Ahead Coordination	IDR	No	Economic	MILP/ CPLEX	Scheduling of MCES involving green hydrogen and renewable energy sources (RESs)
[12]	Herarchical energy management	IDR	No	Technical/ Economic/ Emission	Multi-agent soft actor-critic and deep Q-learning algorithms	Data-driven intelligent scheduling of MCES including RESs and IDR and considering wholesale and retail market signals
[13]	Stochastic Optimization	IDR	No	Economic/ Emission	Non-linearly in Python and optimized using its solvers	Scheduling of MCES with DRP aiming at smoothing load profiles and optimizing the costs allocation
[14]	Optimal energy management	IDR	No	Economic/ Flexibility	Modified Water Evaporation Algorithm (MWEA)	Scheduling of MCES considering the of RESs uncertainty through a two-stage framework
[15]	Probabilistic optimization framework	Dual-sector DR	No	Economic	modified Emperor Penguin Colony algorithm	Scheduling of MCES considering the RESs and DDR through a probabilistic optimization framework and scenario-based modeling
[16]	Energy management	Electric vehicle-based DR	No	Economic/ Emission	Combined Similarity-Navigated Graph Neural Networks (SNGNN) with the Wild Horse Optimization (WHO)	Scheduling of MCES considering unified plug-in electric vehicle-based demand response through a hybrid technique
[17]	Daily programming	IDR	No	Economic	N/A	Scheduling of MCES which RESs uncertainty reduced by a DRP and load shifting
[18]	Flexibility-Constrained Energy Management	IDR	No	Economic/ Emission	MINLP/SCIP Solver	Scheduling of MCES considering electricity and gas utility dependence by peer-to-peer (P2P) energy sharing strategy and IDR
[19]	Optimal operation	Electrical and thermal DR	No	Economic	Hybrid scenario-based/ information gap decision theory (IGDT)	Scheduling of MCES considering consumers satisfaction and two-stage uncertainty method
[20]	Green energy scheduling	Electrical DR	No	Economic	MILP/ CPLEX	Scheduling of MCES considering RESs uncertainty and scenario-based approach
[21]	Stochastic Operation	DR	No	Economic	MILP	Scheduling of MCES considering energy markets in electricity, heating, cooling, gas, and hydrogen
[22]	Optimal scheduling and reconfiguration	Residential IDR	No	Comfort/ Economic	Game theory	Scheduling and reconfiguring of MCES through a three-level framework and the competition among residential DR aggregators
[23]	Optimal scheduling	Electrical and thermal DR	No	Economic	Water wave optimization (WWO)	Stochastic scheduling of MCES with modeling the energy market participation
[24]	Multi-time scale scheduling	Multiple types of DR	No	Economic	analytical method and particle swarm optimization (PSO)	Scheduling of MCES including multiple types of DR and comprehensive incentive mechanism
Proposed	Optimal Scheduling	Electrical/ Heating	Yes	Economic/ Reliability	MILP/ CPLEX	Scheduling of MCES considering behavioral economic concepts in both electricity and heating systems as NBIDR

equipment and network limitations, along with the NBDIR model, as elaborated in the subsequent sections.

2.2 *Problem Formulation*

2.2.1 Objective function

The objective function is represented by Equation (1).

$$Max\ (EB + HB - OC) \quad (1)$$

Equation (1) serves as the objective function, which is derived from a utility perspective and represents the difference between the bill (electricity bill (EB) and heating bill (HB)) and the operation cost (OC). The electricity/heating bill is expressed in equation (2), while the operation cost encompasses the costs associated with the diesel generator (DG) operation, household/customer interruption costs (CIC), as reliability term, for both electricity and heating loads, as well as expenses linked to imported power and natural gas from the upstream network, which are elaborated upon in detail in sources [30]-[32].

2.2.2. Nudge-based Behavioral Integrated Demand Response (NBIDR)

The typical and general formulation of DR in both electrical and heating systems, utilized in this paper, is presented by equations (2) and (3) [13, 14].

$$B(c,t) = (P_L(c,t) - DR(c,t))\pi(c,t),\ \forall c, \forall t \quad (2)$$

$$0 \le DR(c,t) \le P_L(c,t) \forall c, \forall t \quad (3)$$

Customers settle their invoices according to the equation specified in Eq. (2), which corresponds with a time-of-use (TOU) demand response initiative and tariffs. In this equation, (π) is the energy tariff which varies depending on the usage time. In this program, however, (π) can be influenced by various behavioral principles and must be modified according to concepts from behavioral economics and nudge theory as outlined [21]:

• Endowment Effect (EE): Consumers benefit from fixed rates during the day and tend to be connected to their everyday activities, making them less open to changes. To address consumer reluctance, this paper proposes reducing off-peak pricing to zero for load shifted from peak hours, emphasizing that the DR program aims to enhance rather than diminish consumer welfare through free electricity and heating consumption benefits. This approach is designed to motivate consumers to shift their usage from peak to off-peak hours, given the substantial advantages arising from their participation by choice. This concept can be applied by setting prices based on EE as represented by $\pi_{EE}^{Off-Peak}$ in equations (4) and (7).

$$EB(c) = \sum_{t \in T^{Peak}} ((1 - LSI(c,t))P_L(c,t) - DR^{Peak}(c,t))\pi_{SQ}^{Peak}(c,t), \quad (4)$$

$$+ \sum_{t \in T^{Off-Peak}} \begin{matrix} ((1 - LSI(c,t))P_L(c,t))(\pi_{SQ,LA}^{Off-Peak}(c,t)) \\ +(DR^{Off-Peak}(c,t))(\pi_{EE}^{Off-Peak}(c,t)), \end{matrix} \quad ,\forall c \in C_{CF}^{non-e/d/p}$$

$$\sum_{t \in T^{Off-Peak}} DR^{Off-Peak}(c,t) \le \sum_{t \in T^{Peak}} DR^{Peak}(c,t)\ \forall c \in C_{CF}^{non-e/d/p} \quad (5)$$

$$DR^{Peak}(c,t) \le \alpha_{BE}(c,t)P_L(c,t), \forall c \in C_{CF}^{non-e/d/p}, \forall t \in T^{Peak} \quad (6)$$

$$DR^{Off-Peak}(c,t) \le DR^{Peak}(c,t), \forall c \in C_{CF}^{non-e/d/p}, \forall t \in T^{Peak} \quad (7)$$

$$\alpha_{BE}(c) = F(\pi^{Peak}, \pi^{Off-Peak}), \forall c \in C_{CF}^{non-e/d/p} \quad (8)$$

• Status-quo bias (SQ) and Concern for Fairness (CF): Researchers have noted that when a bill featuring a voluntary dynamic tariff is offered as the default option, the majority of consumers tend to retain it. Nonetheless, it is important to recognize that vulnerable households, including the elderly, disabled, and low-income individuals, may lack the capacity to adjust their energy consumption and could suffer disadvantages when dynamic tariffs are set as the default option. In this context, this paper proposes the creation of clusters based on geographical location and customer demographics (such as low-income neighborhoods and buildings with elderly or disabled residents) to modify the default selection in billing, taking into account the idea of status-quo bias. This principle is represented in the pricing model based on SQ as π_{SQ}^{Peak} and $\pi_{SQ}^{Off-peak}$, where a voluntary dynamic tariff is offered as a default in equation (4). Additionally, the formation of clusters according to geographical areas and customer categories (elderly, disabled, and low-income individuals) is indicated as $\forall c \in C_{CF}^{non-e/d/p}$, which is executed to modify the default selection in billing through equations (4)-(7).

• Loss Aversion (LA): Customers are concerned about more losses than gains. This intense fear of losing something can result in illogical actions and choices. As a result, higher rates during peak times in a DRP lead to customer dissatisfaction and discourage them from participating. However, this sentiment can be offset and enhanced by significantly lowering off-peak tariffs to motivate customers to participate in DRPs [33]. This concept is represented by pricing that is determined by SQ as $\pi_{SQ,LA}^{Off-Peak}$, which results in a considerable reduction in tariffs of off-peak hours modeled in (4). In general, customers may display varying patterns in load reduction (DR), which can be represented by a coefficient that changes based on both the time of use and the type of customer. In fact, α_B is defined as a coefficient that can be considered as a function of π, which, with proper design and marketing of the dynamic tariffs from the utility side based on the BE principle, can increase participation to a maximum percentage from the customer side. Furthermore, α_B is also considered a function of the customer's type (8). In this paper α_{BE} is regarded as:

$$\alpha_{BE}(c) = 1 - \left(\left[\frac{\sum_{t \in T^{Off-Peak}} \pi^{Off-Peak}(c,t)}{TT^{Off-Peak}} \right] / \left[\frac{\sum_{t \in T^{Off-Peak}} \pi^{Peak}(c,t)}{TT^{Peak}} \right] \right)$$

In α_{BE}, $TT^{Off-Peak}$ and TT^{Peak} represent the overall peak and off-peak hours during the operational period.

2.2.3. MCES Constraints

This section outlines the limitations related to natural gas networks, the electricity grid, and the equipment/components within the MCES.

The AC optimal power flow (ACOPF) constraint equations (9)-(14) are used for modeling electricity networks [34], [35].

$$\sum_{i\in S_m^i} PI_E(t)+\sum_{w\in S_m^w} P_W(w,t)+\sum_{pv\in S_m^{pv}} P_{PV}(pv,t)+\sum_{s\in S_m^s} P_{ES}(s,t) + \sum_{ch\in S_m^{ch}} P_{CHP,E}(ch,t)-\sum_{c\in S_m^l}(1-LSI_E(c,t))P_{L,E}(c,t) - DR^{Peak,E}(c,t)+DR^{Off-Peak,E}(c,t)) = \sum_{n=1}^{N_m} P_{EL}(m,n,t), \forall m,t \quad (9)$$

$$\sum_{i\in S_b^i} QI_E(t)+\sum_{w\in S_b^w} Q_W(w,t)+\sum_{pv\in S_b^{pv}} Q_{PV}(pv,t))+\sum_{s\in S_b^s} Q_{ES}(s,t) - \sum_{c\in S_b^c}(1-LSI_E(c,t))Q_{L,E}(c,t)=\sum_{c=1}^{N_B} Q_{EL}(m,n,t), \forall b,t \quad (10)$$

$$P_{EL}(m,n,t)=G(m,n)(V(m,t)+V(n,t))+B(m,n)(\delta(m,t)-\delta(n,t)) \quad (11)$$

$$Q_{EL}(m,n,t)=B(m,n)(V(m,t)+V(n,t))+G(m,n)(\delta(m,t)-\delta(n,t)) \quad (12)$$

$$(P_{EL}(m,n,t)^2+(Q_{EL}(m,n,t))^2 \le (S_{EL}{}^{\max}(m,n,t))^2 \quad \forall m,n\in S^{eline},t \quad (13)$$

$$a_i Q_{EL}+b_i P_{EL}+c_i=0 \qquad \forall i\in\{1,2,\ldots,8\} \quad (14)$$

The balance of active power in Eq. (9) includes contributions from photovoltaic units (PVs), wind turbine units (WTs), combined heating and power units (CHPs), and electrical storage units (ESs), represented by $P_{PV}, P_W, P_{CHP,E}, P_{ES}$, respectively. $P_{L,E}$ reflects the electricity demand as indicated by Eq. (9). Similarly, the balance for reactive power generation (Q) is modeled through Eq. (10). The thermal limits ($S_{EL}{}^{\max}$) for P_{EL} and Q_{EL} , which represent the active and reactive line flows, are defined by a linear formulation represented in Eqs. (11)-(14). In this context, B and G refer to the susceptance and conductance of the line, V denotes the voltage magnitude, and δ represents the angle of the buses (b).

Additionally, the estimated representation for the natural gas network is outlined in equations (15) and (16) [30]-[32], where P_{pip} represents the flow of gas through the pipelines, while $P_{gas,chp}, P_{gas,bo}$ denote the gas consumption by CHPs and boilers (Bs) at each bus. Additionally, at each bus, the heating balance equation among boilers (P_{BO}), CHPs ($P_{CHP,H}$), heating storage units (HSs) (P_{HS}), and the heating load ($P_{L,H}$) is maintained as per Eq. (17).

$$P_{pip}(m,n,t)=GHV\ f(m,n,t)\forall m,n\in S^{gline},t \quad (15)$$

$$(P_{gas,chp}(m,t)+P_{gas,bo}(m,t))=\sum_{n\in S_m^{gline}} P_{pip}(m,n,t)\,\forall m,t \quad (16)$$

$$\sum_{ch\in S_m^{ch}} P_{CHP,H}(ch,t)+\sum_{bo\in S_m^{bo}} P_{BO}(bo,t)+\sum_{sh\in S_m^{sh}} P_{HS}(sh,t) - \sum_{l\in S_m^l} P_{L,H}(c,t)=0, \forall m,t \quad (17)$$

The power generated by WTs and PVs is characterized in references [30], [31]. The operational limitations of ESs and HSs differ during charging and discharging phases, as outlined in references [30], [31]. The operational limitations of combined CHPs are defined and discussed in references [30], [31]. The operational constraints for BSs are taken into account as mentioned in references [30], [31].

3. Implementation and Results

3.1. Problem Solution

In this study, the suggested MILP model is implemented on the IEEE 33-bus distribution test system. The CPLEX 12.2 solver within the generalized algebraic modeling systems (GAMS) software is employed to efficiently solve the suggested MILP formulations [36] on a personal Core i3 PC with a configuration of a 2.5GHz CPU and 4GB of RAM. The simulation incorporates a TOU plan for Southern California Edison (SCE), where electricity rates vary from 36 to 71 cents per kWh from 2 PM to 9 PM each day [37]. In the IEEE 33-bus distribution test system, each bus is considered to represent a grouping of buildings, with clusters 1 to 3 corresponding to elderly, disabled, and low-income individuals. Additional data and modified parameters for the network and its components can be found in references [30]-[32], [38], [39].

3.2. Results

Three scenarios are formulated to evaluate the performance of the proposed model, as detailed below.

- **Scenario 1:** Optimal Scheduling of MCES, Without Demand Response (DR)
- **Scenario 2:** Optimal Scheduling of MCES, With Nudge-based Behavioral Electricity Demand Response (NBEDR)
- **Scenario 3:** Optimal Scheduling of MCES, With Nudge-based Behavioral Integrated (Electricity and Heating) Demand Response (NBIDR)

3.2.1. Optimal Scheduling of MCES, Without DR

Table II. Outcomes of Scenario 1.

Costs	(¢)
OC	935767.819
EB	2493051.967
HB	1159619.854
ECIC	333508.545
HCIC	100358.919
IPCost	174692.936
IGASCost	195109.859
Electricity	**(kWh)**
$P_{CHP,E}$	21103.196
P_{PV}	3652.561
P_{WT}	7539.627
P_{DG}	15997.379
P_I	24019.213
NBEDR	0
EENS	2779.238
Heating	**(kWh)**
$P_{CHP,H}$	23615.481
P_{BO}	12572.277
NBHDR	0
HENS	1672.649

Table II displays the outcomes of the simulation for scenario 1. According to Table II, operating the multi-carrier energy system without demand response resulted in an operation cost (OC) of $9357 and bills for electricity and heating of $24930 and $11596. Additionally, the cost of interruption in this scenario is approximately $3335 and $1003 for electricity and heating systems, respectively. Moreover, the payments for imported power and gas from the upstream grid, namely imported power cost (IPCost) and imported gas cost (IGASCost), amount to $1746 and $1951, respectively.

3.2.2. Optimal Scheduling of MCES, With NBEDR

Table III. Outcomes of Scenario 2.

Costs	(¢)
OC	767828.337
EB	2510062.378
HB	1159619.854
ECIC	127631.194
HCIC	100358.919
IPCost	171674.431
IGASCost	191859.886
Electricity	**(kWh)**
$P_{CHP,E}$	20085.442
P_{PV}	3652.561
P_{WT}	7539.627
P_{DG}	21377.528
P_{I}	21618.457
NBEDR	1352.207
EENS	1063.593
Heating	**(kWh)**
$P_{CHP,H}$	22476.566
P_{BO}	13711.193
NBHDR	0
HENS	1672.649

Table IV. Outcomes of Scenario 3.

Costs	(¢)
OC	681288.641
EB	2519846.260
HB	1172131.623
ECIC	146461.972
HCIC	≈ 0
IPCost	168521.966
IGASCost	199263.974
Electricity	**(kWh)**
$P_{CHP,E}$	20555.373
P_{PV}	3652.561
P_{WT}	7539.627
P_{DG}	20240.153
P_{I}	22050.663

Table III presents the numerical outcomes from the simulation of scenario 2. As shown in Table III, operating the multi-carrier energy system with NBEDR resulted in an operation cost of $7678 ,and bills for electricity and heating of $25100 and $11596, respectively, representing daily utility income. Additionally, the CIC for this scenario is approximately $1276 and $1003 for electricity and heating systems, respectively. Additionally, the expenses for power imported from the upstream grid, referred to as IPCost, amount to $1716, while the costs for imported gas, known as IGASCost, are $1918.

3.2.3. Optimal Scheduling of MCES, With NBIDR

Table IV shows the numerical outcomes of scenario 3, which is the optimal scheduling of MCES with NBIDR. As shown in Table IV, NBIDR implementation in optimal scheduling of the multi-carrier energy system results in an operation cost of $7678. Furthermore, the electricity and heating bills, representing daily utility income, reach $25100 and $11596, respectively. Additionally, the electricity and heating CIC are approximately $1276 and $1003, respectively, for the proposed integrated system. The costs for imported electricity and gas from the upstream grid, known as IPCost and IGASCost, are $1716 and $1918, respectively.

4. Discussions and Analysis

In this part, the effects of implementing NBIDR are examined in relation to the economic and technological aspects of the scenarios being examined, focusing on the operational conditions such as total lost load, operation costs, and the performance of customers in load shifting and peak shaving.

Recently, utilities, policymakers, and researchers have evaluated various systems for implementing time-varying tariff programs. However, the practical success of DR initiatives depends primarily on customer behavior. Specifically, the implementation of DR, which impacts customer comfort, is considerably influenced by their inclinations and prejudices. Consequently, DR models assuming rational economic behavior often show significant discrepancies between predictions and actual program outcomes. Utilizing behavioral economics (BE) and its principles can serve as an effective approach to address this challenge, as it incorporates psychological insights into economic modeling [33].

This study seeks to incorporate BE principles into the modeling of the DR program for both electricity and heating systems, particularly the TOU program. It has been achieved by applying key BE concepts, including EE, SQ, CF, and LA, as NBIDR. As illustrated in Fig. 1, the suggested NBIDR within a multi-carrier energy framework leads to acceptable performance in shifting load from peak to off-peak hours. Furthermore, as represented by Fig.2, the proposed novel program contributes to peak shaving and improves and smooths the electricity and heat load shape. In contrast, electricity and heat bills as revenues for utilities have held and even improved. Furthermore, simulation results demonstrate that incorporating BE principles in DR modeling, as NBIDR, especially during peak periods, can play a crucial role in achieving optimal and efficient scheduling and operations from the utilities' perspective. Moreover, as shown in Figs. 3 and 4, enhanced customer engagement in DRPs in the NBDIR framework, leads to more than a

55% reduction in CIC and EENS for the electricity system. Furthermore, EENS and CIC for the heating system reached almost zero. Reducing CIC, along with the reduction in importing power from the main grid and the generation of CHPs, particularly during peak times, results in a substantial decrease in OC.

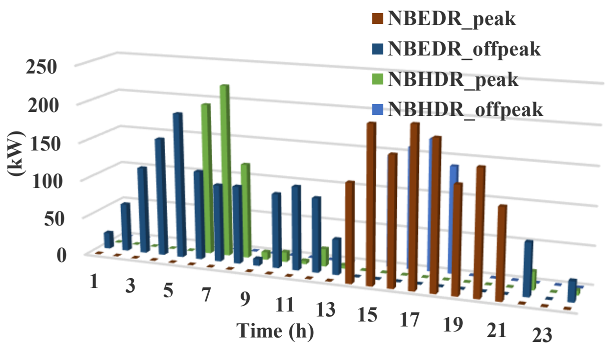

Fig. 1. Consumers' performance in the NBIDR program in shifting load from peak to off-peak hours.

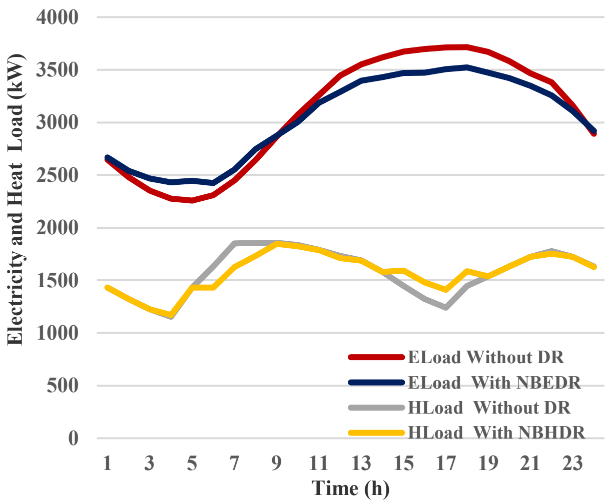

Fig. 2. Load shape without and with employing NBIDR.

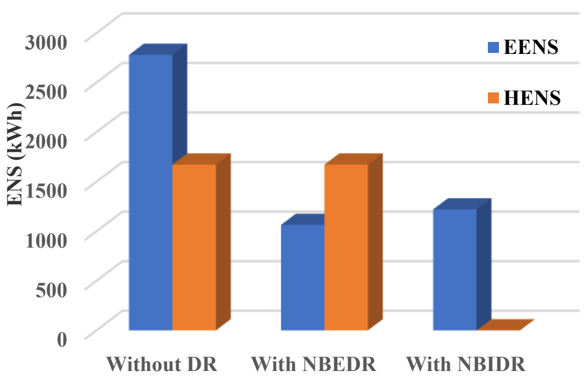

Fig. 3. Energy not supplied and reliability evaluation without and with employing NBIDR.

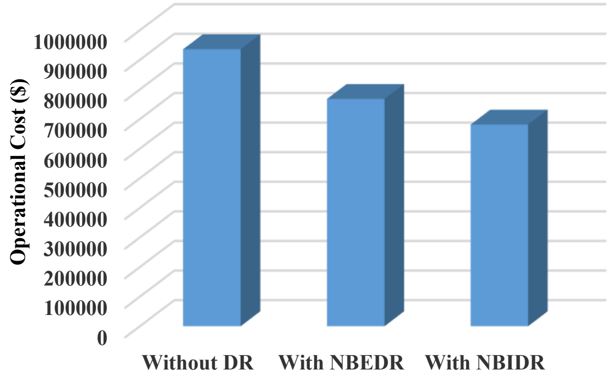

Fig. 4. Total operating expenses with and without the use of NBIDR.

Notably, the economic implications of implementing NBIDR extend beyond simple cost reductions to encompass fundamental shifts in utility revenue structures and operational paradigms. The observed 27% reduction in OC represents a substantial financial benefit that can be attributed to several interconnected factors. Furthermore, customer participation in DRPs creates a more predictable load profile, allowing utilities to optimize their generation portfolio and reduce reliance on expensive peaking units, and, through more efficient operational conditions, reduce wear on equipment and its subsequent costs. Furthermore, 4% decrease in electricity imports from the main grid demonstrates increased energy independence at the distribution level, which mostly consists of RESs, which not only reduces local market price but also enhances price stability for end consumers. Additionally, the successful implementation of behavioral economics principles in DRPs creates a foundation for more sophisticated energy market mechanisms, potentially leading to more efficient price signals and improved resource allocation across the entire energy ecosystem.

On the other hand, the dramatic 55% reduction in customer interruption costs represents one of the most significant economic achievements of the proposed framework. This improvement directly translates to enhanced service reliability, which carries substantial economic value for both utilities and consumers. From the utility perspective, reduced interruption costs lower the financial liability associated with service disruptions, thereby improving overall profitability and reducing insurance premiums. Furthermore, for consumers, improved reliability means fewer productivity losses, reduced equipment damage, and enhanced quality of life. The economic ripple effects of this improvement extend to the broader economy, as a reliable energy supply supports industrial productivity and commercial activities. The cumulative effect of these improvements suggests that NBIDR can catalyze broader economic transformation within the energy sector.

5. Conclusion

This study utilizes principles from behavioral economics to examine a demand response initiative referred to as nudge-based behavioral integrated demand response (NBDIR). This research incorporates several behavioral economics concepts (endowment effect, status-quo bias, concern for fairness, and loss aversion) to achieve positive reinforcement in DR modeling and application while influencing household and customer decision-making in both electricity and heating systems. In this context, an optimal scheduling framework for multi-carrier energy systems is proposed that incorporates NBIDR, which combines behavioral principles into a DR program for both electricity and heating systems. Simulation findings indicate that the proposed model significantly reduces operation costs, electricity, and heating load interruption, as well as imported power from the main upstream grid. The economic ripple effects of this improvement extend to the broader economy, as a reliable energy supply supports industrial productivity and commercial activities. The cumulative effect of these improvements suggests that NBIDR can serve as a catalyst for broader economic transformation within the energy sector.

6. References

[1] J. Wang, H. Zhong, Z. Ma, Q. Xia, C. Kang, "Review and prospect of integrated demand response in the multi-energy system," Applied Energy, vol. 202, pp. 772–782, 2017.

[2] W. Huang, N. Zhang, C. Kang, M. Li, M. Huo, "From demand response to integrated demand response: Review and prospect of research and application," Protection and Control of Modern Power Systems, vol. 4, no. 2, pp. 1–13, 2019.

[3] M. Vahid-Ghavidel, M.S. Javadi, M. Gough, S.F. Santos, M. Shafie-Khah, J.P. Catalao, "Demand response programs in multi-energy systems: A review," Energies, vol. 13, no. 17, p. 4332, 2020.

[4] H. Chen, S. Yang, J. Chen, X. Wang, Y. Li, S. Shui, H. Yu, "Low-carbon environment-friendly economic optimal scheduling of multi-energy microgrid with integrated demand response considering waste heating utilization," Journal of Cleaner Production, vol. 450, p. 141415, 2024.

[5] A. Kumar, A. Maulik, K.A. Chinmaya, "A decentralized energy management scheme for a DC microgrid with correlated uncertainties and integrated demand response," Electric Power Systems Research, vol. 238, p. 111093, 2025.

[6] X. Lu, K. Zhou, "A distributionally robust optimization approach for optimal load dispatch of energy hub considering multiple energy storage units and demand response programs," Journal of Energy Storage, vol. 78, p. 110085, 2024.

[7] H. Nourizadeh, M.S. Nazar, "Customer-oriented scheduling of active distribution system considering integrated demand response programs and multi-carrier energy hubs," Journal of Cleaner Production, vol. 447, p. 141308, 2024.

[8] A. Darvishi, B. Ranjbar, R. Gharibi, R. Khalili, R. Dashti, "Multi-objective optimization of a socio-economic energy hub with demand response program and considering customer satisfaction," Journal of Energy Storage, vol. 100, p. 113624, 2024.

[9] G. Wang, C. Pan, W. Wu, J. Fang, X. Hou, W. Liu, "Multi-time scale optimization study of integrated energy system considering dynamic energy hub and dual demand response," Sustainable Energy, Grids and Networks, vol. 38, p. 101286, 2024.

[10] C. Yang, Z. Wu, X. Li, A. Fars, "Risk-constrained stochastic scheduling for energy hub: Integrating renewables, demand response, and electric vehicles," Energy, vol. 288, p. 129680, 2024.

[11] M.M. Amiri, M.T. Ameli, M.R. Aghamohammadi, E. Bashooki, H. Ameli, G. Strbac, "Day-Ahead Coordination for Flexibility Enhancement in Hydrogen-Based Energy Hubs in presence of EVs, Storage, and Integrated Demand Response," IEEE Access, 2024 (in press).

[12] A. Khodadadi, S. Adinehpour, R. Sepehrzad, A. Al-Durra, A. Anvari-Moghaddam, "Data-Driven hierarchical energy management in multi-integrated energy systems considering integrated demand response programs and energy storage system participation based on MADRL approach," Sustainable Cities and Society, vol. 103, p. 105264, 2024.

[13] Babajani-Chari, M.A. and Ghasemi-Marzbali, A., 2025. Stochastic Optimization of a Multi-Carrier Energy System with the Participation of Renewable Energy Sources and Integrated Demand Response Programs. *Scientia Iranica*.

[14] Garg, A., Niazi, K.R., Tiwari, S., Sharma, S. and Rawat, T., 2025. Optimal energy management of multi-carrier energy system considering uncertainty in renewable generation. *Scientific Reports*, *15*(1), p.25936.

[15] Hu, Y. and Jin, Y., 2025. Energy Hubs Integrating Renewable Energy Sources and Demand Response Programs for Cost-Effective Operations. *Energy*, p.137271.

[16] Karthikeyan, A. and Arun, V., 2025. Enhancing energy hub management with unified plug-in electric vehicle based demand response and energy storage systems. *Journal of Energy Storage*, *108*, p.114997.

[17] Zhang, L. and Liu, Y., 2025. Reducing Uncertainty in Energy Hub Operation: A Demand Response Approach for Improved Cost-Efficiency. *Journal of Energy Resources Technology, Part A: Sustainable and Renewable Energy*, *1*(4), p.041701.

[18] Riki, A., Oukati Sadegh, M. and Narouei, O., 2025. Flexibility-constrained energy management of smart energy hubs considering Peer to Peer transactive energy and Demand Response program. *International Journal of Industrial Electronics Control and Optimization*, *8*(1), pp.67-82.

[19] Yarmohammadi, H. and Abdi, H., 2024. Optimal operation of multi-carrier energy systems considering demand response: A hybrid scenario-based/IGDT uncertainty method. *Electric Power Systems Research*, *235*, p.110877.

[20] Rajaei, A., Rashidinejad, M., Afzali, P. and Dorahaki, S., 2024. Empowering sustainable energy communities: Optimizing multi-carrier energy systems with green energy, uncertainty management, and demand response. *e-Prime-Advances in Electrical Engineering, Electronics and Energy*, *8*, p.100560.

[21] Ahmadi, S. and Nazar, M.S., 2025, February. Stochastic Day-Ahead Economic Operation Scheduling of Multi-Carrier Microgrids Considering Energy Markets and Demand Response. In 2025 12th Iranian Conference on Renewable Energies and Distributed Generation (ICREDG) (pp. 1-6). IEEE.

[22] Nourizadeh, H. and Nazar, M.S., 2025. Optimal day-ahead scheduling and reconfiguration of active distribution systems considering energy hubs, residential demand response aggregators, and electric vehicle parking lot aggregators. *Computers and Electrical Engineering*, *123*, p.110227.

[23] Jiang, W., Wang, X., Huang, H., Zhang, D. and Ghadimi, N., 2022. Optimal economic scheduling of microgrids considering renewable energy sources based on energy hub model using demand response and improved water wave optimization algorithm. *Journal of Energy Storage*, *55*, p.105311.

[24] Wang, L., Lin, J., Dong, H., Wang, Y. and Zeng, M., 2023. Demand response comprehensive incentive mechanism-based multi-time scale optimization scheduling for park integrated energy system. *Energy*, *270*, p.126893.

[25] M. Nozarian, M. Namazizadeh, "Nudge-Based Demand Response (NBDR): Employing Behavioral Economics Principles Towards Optimal Operation of Multi-Carrier Energy Systems," In 14th Smart Grid Conference (SGC), Dec. 2024, IEEE, pp. 1–5.

[26] R. Thaler, C. Sunstein, Nudge: Improving decisions about health, wealth and happiness, Amsterdam Law Forum; HeinOnline, 2008, p. 89.

[27] M. Kosters, J. Van der Heijden, “From mechanism to virtue: Evaluating Nudge theory,” Evaluation, vol. 21, no. 3, pp. 276–291, 2015.
[28] C.W. Cai, “Nudging the financial market? A review of the nudge theory,” Accounting & Finance, vol. 60, no. 4, pp. 3341–3365, 2020.
[29] M.G. Pollitt, I. Shaorshadze, “The role of behavioural economics in energy and climate policy,” In Handbook on Energy and Climate Change, Edward Elgar Publishing, pp. 523–546, 2013.
[30] M. Nozarian, A. Fereidunian, A. Hajizadeh, “An operationally induced approach to reliability-oriented ACOPF-constrained planning of interconnected multi-carrier energy hubs: An MILP formulation,” Sustainable Energy Technologies and Assessments, vol. 57, p. 103196, 2023.
[31] M. Nozarian, A. Fereidunian, “Analysis of Emergent Behavior of Reliability in the System of Systems Including Energy Hubs,” Journal of Modeling in Engineering, vol. 19, no. 66, pp. 1–21, 2021.
[32] M. Nozarian, A. Fereidunian, M. Barati, “Reliability-oriented planning framework for smart cities: From interconnected micro energy hubs to macro energy hub scale,” IEEE Systems Journal, vol. 17, no. 3, pp. 3798–3809, 2023.
[33] M.A. Andor, K.M. Fels, “Behavioral economics and energy conservation – a systematic review of non-price interventions and their causal effects,” Ecological Economics, vol. 148, pp. 178–210, 2018.
[34] A. Karimi, F. Aminifar, A. Fereidunian, H. Lesani, “Energy storage allocation in wind integrated distribution networks: An MILP-Based approach,” Renewable Energy, vol. 134, pp. 1042–1055, 2019.
[35] M. Nozarian, A.H. Nikoofard, A. Fereidunian, “Efficient MILP formulations for AC optimal power flow to reduce computational effort,” International Transactions on Electrical Energy Systems, vol. 30, no. 8, p. 12434, 2020.
[36] “Generalized Algebraic Modeling Systems (GAMS),” [Online]. Available at: http://www.gams.com/.
[37] “Solar Learning Center, The Pros and Cons of Rooftop Solar in 2024, Time of Use Rates, Your TOU Rates Guide” [Online]. Available at: https://www.solar.com/learn/time-of-use-rates/
[38] M.H. Shams, M. Shahabi, “Optimal Operation Scheduling of a Microgrid in Presence of Energy Hubs Considering Energy System Security and Demand Response,” Tabriz Journal of Electrical Engineering, vol. 47, no. 4, pp. 1523–1535, 2018 (in Persian).
[39] A. Fallahsabet, M. Nozarian, A. Fereidunian, “Resiliency-Oriented Planning of Smart City Energy Infrastructure, Considering Energy Hubs, Based on Prioritized Critical Loads,” In 8th International Conference on Technology and Energy Management (ICTEM), Feb. 2023, IEEE, pp. 1–6.