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Nonlinear demand response programs for residential customers with nonlinear behavioral models

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ABSTRACT

To mitigate environmental issues of the thermal power plants, their greenhouse gas emissions are factored into the unit commitment (UC) problem. Moreover, demand side management as an effective strategy can relieve the energy security and environmental issues. Thus, the residential customers as one of the major groups of the customers, should be incorporated in the UC and generation scheduling problems. In this study, implementation of demand response (DR) programs in the UC problem are modeled. Herein, the implemented DR programs are entitled nonlinear DR (NDR) programs because nonlinear behavioral models for the residential customers are considered. In addition, the value of cost correlated with the implementation of the NDR programs in the UC problem (UC-NDR) are modeled. It is demonstrated that cooperation of the residential customers in the UC-NDR problem can be beneficial in decreasing cost and greenhouse gas emissions of the thermal power plants. In addition, it is concluded that comprehensive studies are needed to realistically model the residential customers behavior, since the different behavioral models result in different solutions and outcomes for the UC-NDR problem.

1. Introduction

A major part of the environmental concerns is caused by burning fossil fuel in the thermal power plants and emitting several contaminants into the atmosphere [1]. Fig. 1 illustrates the rised greenhouse gas emissions from a thermal power plant in Gelsenkirchen, Germany [2]. A new regulation has been adopted by the Clean Air Act Amendment to force the utilities to modify their design or operational strategies for reducing pollution and atmospheric emissions of their thermal power plants [3]. Thus, the fuel consumption and greenhouse gas emissions level of the thermal power plants must be simultaneously taken into consideration in the unit commitment (UC) problem. The problem of UC involves finding the least-cost dispatch of available generation resources (e.g., thermal power plants) to meet the electrical load. In fact, converting the greenhouse gas emissions of the each thermal power plant into the greenhouse gas emissions cost function and merging it into the UC problem is able to mitigate the environmental issues of the thermal power plants [4].

Demand side management (DSM) is considered as the first precedence in all the energy policy decisions due to its benefits from economic and environmental viewpoints [5,6]. DSM provides short-term responses to electricity market conditions to reduce overall costs of energy supply, increase reserve margin, and mitigate price volatility [5]. Also, it achieves environmental goals by deferring commitment of polluted units leading to increased energy efficiency and reduced greenhouse gas emissions [5].

Several studies have investigated the implementation potential of demand response (DR) programs [7–9]. The U.S. federal energy regulatory commission estimates that the contribution from the existing customers in the U.S. is around 41,000 MW equal to 5.8% of the 2008 summer peak demand [7]. A study presented in Ref. [8] shows that incentive-based programs (IBPs) are responsible for 93% of peak load reduction in the U.S. The studies presented in Refs. [9–13], have investigated the effects of DR programs on the residential customers demand.

Nowadays, considering presence of residential customers in the generation scheduling and UC problems is mandatory due to active participation of residential customers in the power market and DR programs. Some papers have investigated DR programs in the UC and generation scheduling problems [14–20]. In Ref. [14], the authors have determined value of demand to be shifted from peak period to other periods by direct load control for congestion management and increasing utilization of wind power. The authors in Ref. [15], have implemented DR program in the UC problem to increase the amount of wind power that can be economically injected to the system. In this paper, the responsive customers are

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Nomenclature

A. Indices and sets

$\phi \in S_\phi$ Residential customers' class
$\delta \in S_\delta$ DR program
$g \in S_g$ Generation unit
$t \in S_t$ Hour
$\xi \in S_\xi$ Responsive customer behavioral model

B. System parameters and variables

$C^{\delta}_{\phi,\xi}(.)$ DR program implementation cost for residential customers in class ϕ with behavioral model ξ
$C^{\delta}_{Tot}(.)$ DR program implementation cost for all classes of residential customers
$C^{F}_{g}(.)$ Fuel cost of unit g
$C^{E}_{g}(.)$ Greenhouse gas emissions cost of unit g
c^{STU}_{g} Start-up cost of unit g
c^{SHD}_{g} Shut down cost of unit g
$D^{0}_{\phi,\xi}(.)$ Initial demand of residential customers in class with behavioral model ξ
$D^{\delta}_{\phi,\xi}(.)$ Demand of residential customers in class ϕ with behavioral model ξ after implementation of NDR program
$E_{\phi}(.,.)$ Price elasticity of demand of residential customers
$I^{EDRP}(.)$ Value of incentive in EDRP
MDT_g, MUT_g Minimum down time and minimum up time of unit g, respectively
$OFFT_g$, ONT_g Number of hours that unit g has been kept "off" and "on", respectively
$P_g(.)$ Generation of unit g
P^{min}_{g}, P^{max}_{g} Minimum and maximum generation of unit g
RDR_g, RUR_g Ramp down rate and ramp up rate of unit g, respectively
SR Spinning reserve amount
x^{EDRP} Incentive as variable of EDRP
x^{TOU} Price regulator as variable of TOU
$y^{CS}_{g}(.)$ Binary variable as commitment status of unit g
$y^{\delta}(.)$ Binary variable as indicator for implementation of NDR program
$\pi^{0}(.)$ Initial price of electricity
$\pi^{TOU}(.)$ Price of electricity after implementation of TOU program
$\alpha^{F}_{1,g}$, $\alpha^{F}_{2,g}$, $\alpha^{F}_{3,g}$ Fuel cost coefficients of unit g
$\alpha^{E}_{1,g}$, $\alpha^{E}_{2,g}$, $\alpha^{E}_{3,g}$ Greenhouse gas emissions level coefficients of unit g
β^{E} Greenhouse gas emissions cost factor

C. SA algorithm parameters and variables

N^{SA} Number of generating new state at every temperature
p_k Adaptive probability for acceptance of new solution at stage k
r_k Random number in range of [0,1) at stage k
y^{SA}_{k} Binary variable as indicator for acceptance of new solution at stage k
μ Coefficient for gradually decreasing temperature of molten metal
ε_k Internal energy of molten metal at stage k
θ_0 Initial temperature of molten metal
θ_k Temperature of molten metal at stage k

Fig. 1. The rised greenhouse gas emissions from a thermal power plant in Gelsenkirchen, Germany [2].

linked to the hourly market prices and their loads are curtailed or shifted to other hours.

However, in the above mentioned studies, the behavior of responsive customers with respect to the different strategies of DR program designer have not been modeled in the problem. In Refs. [16–18], a model for cooperation of risk-cost based UC with customers, considering linear model for the responsive customers behavior, has been presented. In Ref. [19], nonlinear models of responsive customers behavior and nolinear DR (NDR) programs have been investigated in some real power markets. However, the NDR programs have not been implemented in the UC problem (UC-NDR). In addition, the implementation cost of the NDR program have not been modeled.

In this study, NDR programs are investigated in the UC-NDR problem considering different nonlinear behavioral models for the responsive customers behavior and greenhouse gas emissions of the thermal power. Herein, nonlinear emergency demand response program (EDRP) as the voluntary IBP and nonlinear time of use (TOU) program as the voluntary time-based rate (TBR) program are applied in the UC problem to form the UC-NEDRP and UC-NTOU problems, respectively. In EDRP, the responsive customer receives incentive because of demand reduction at peak period [20–22]. Also, in TOU program, value of the price of electricity are different at different periods of the day [20–22]. In other words, the electricity price at valley, off-peak, and peak periods are low, moderate, and high, respectively. The voluntary DR programs have the advantage of neither requiring a bidirectional communication interface, nor knowledge of residential customers' information. The recent studies indicate a reluctance among participants of mandatory DR programs due to the inconvenience caused by interruption of power [20]. Herein, the aim of the UC-NDR problem is to design the optimal scheme for the implementation of the NDR program to minimize the total cost of the problem that includes cost of power generation, cost of greenhouse gas emissions, and cost of NDR program implementation. Moreover, the explicit NDR program implementation cost modelings considering nonlinear behavior of the responsive customers behavior are presented in this study.

The rest of the paper is outlined as follows. In Section 2, the UC-NDR formulation is presented and described. The NDR models are presented in Section 3. In Section 4, an optimization method for solving the UC-NDR problem is presented. Numerical studies and sensitivity analyses carried out are explained in Section 5. Finally, the conclusion is given in Section 6.

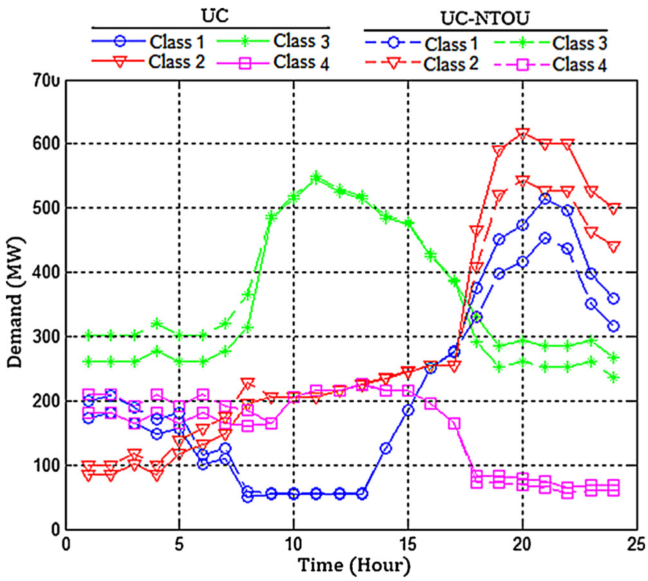

Fig. 2. Hourly demand of the residential customers' classes 1–4 with different behavioral models in the UC and optimal UC-NTOU (MW).

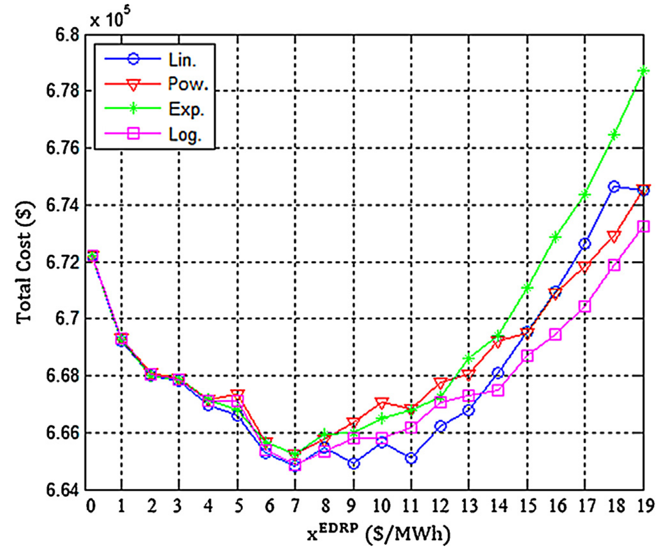

Fig. 3. Sensitivity analysis for the total cost of the UC-NEDRP problem respect with the value of the EDRP variable considering different models for the responsive customers behavior.

2. UC-NDR formulation

2.1. Objective function

The objective function of the UC-NDR over the operation period (one day) is presented in Eq. (1). As can be seen, it includes fuel cost of the generation units, greenhouse gas emissions cost of the generation units, start-up cost of the de-committed units, shut down cost of the committed units, and total implementation cost of the NDR program.

$$F_{op} = \sum_{t \in S_t} \{ \sum_{g \in S_g} C_g^F(t) + C_g^E(t) + C_g^{STU}(t) + C_g^{SHD}(t) \} + C_{Tot}^{\delta}(t), S_t = \{1, \ldots, Nt\}, S_g = \{1, \ldots, Ng\} \quad (1)$$

2.2. Cost terms

In the following, different cost terms of the objective function are described.

2.2.1. Fuel cost

The fuel cost of every generation unit (C_g^F), which is in "on" status ($y_g^{CS} = 1$), is considered a quadratic polynomial as Eq. (2). In other words, the generation unit consumes more fuel per power unit when its power is in the upper level compared to the value of consumed fuel for generating power unit in the lower level of power.

$$C_g^F(t) = (\alpha_{1,g}^F \times (P_g(t))^2 + \alpha_{2,g}^F \times (P_g(t)) + \alpha_{3,g}^F) \times y_g^{CS}(t), \forall t \in S_t, \forall g \in S_g \quad (2)$$

2.2.2. Greenhouse gas emissions cost

The greenhouse gas emissions cost of every generation unit (C_g^E), which is in "on" status ($y_g^{CS} = 1$), is assumed a quadratic polynomial as Eq. (3). The value of emitted greenhouse gas by the generation unit in the upper and lower levels of the generated power follows the same trend for the value of consumed fuel by the generation unit.

$$C_g^E(t) = \beta^E \times (\alpha_{1,g}^E \times (P_g(t))^2 + \alpha_{2,g}^E \times (P_g(t)) + \alpha_{3,g}^E) \times y_g^{CS}(t), \forall t \in S_t, \forall g \in S_g \quad (3)$$

2.2.3. Start-up cost and shut down cost

The start-up cost of every de-committed unit and shut-down cost of every committed unit at every hour of the operation period are presented in Eqs. (4) and (5), respectively. In other words, starting a generation unit up and shuting a generation unit down are not free and have some cost.

$$C_g^{STU}(t) = c_g^{STU} \times (1 - y_g^{CS}(t-1)) \times y_g^{CS}(t), \forall t \in S_t, \forall g \in S_g \quad (4)$$

$$C_g^{SHD}(t) = c_g^{SHD} \times y_g^{CS}(t-1) \times (1 - y_g^{CS}(t)), \forall t \in S_t, \forall g \in S_g \quad (5)$$

2.2.4. Nonlinear demand response program implementation cost

The total implementation cost of NDR program at every hour of the operation period is sum of the NDR program implementation costs for different residential customers' classes with various models presented in Eq. (6). NDR programs include nonlinear EDRP and nonlinear TOU program. Implementation cost of EDRP is related to the value of incentive paid to the residential customers for their demand reduction at peak period. Moreover, implementation cost of TOU program is result from the value of cost/profit when the income of the sold energy is decreased/increased after implementation of this program.

$$C_{Tot}^{\delta}(t) = \sum_{\phi \in S_\phi} \sum_{\xi \in S_\xi} C_{\phi,\xi}^{\delta}(t), \forall t \in S_t, \forall \delta \in S_\delta$$
$$S_\phi = \{1, \ldots, N_\phi\}, S_\xi = \{Pow, Exp, Log, Lin\}, S_\delta = \{EDRP, TOU\} \quad (6)$$

2.3. Problem constraints

In the following, the power system and the generation units' constraints are presented and explained.

2.3.1. System power balance constraint

The power balance constraint of the system that must be held in every time step of the operation period and for any NDR program

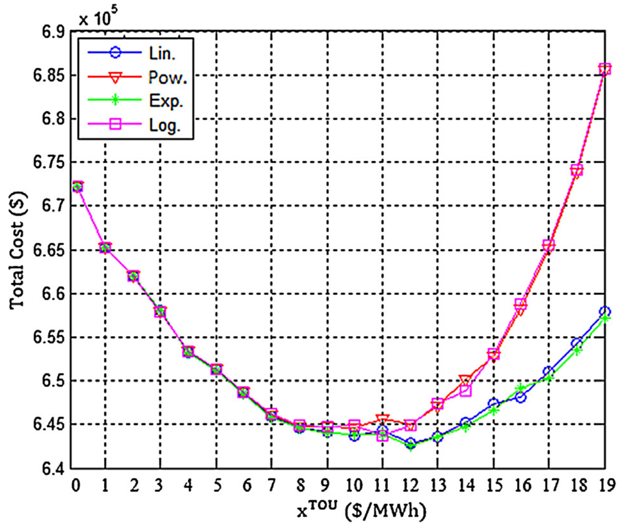

Fig. 4. Sensitivity analysis for the total cost of the UC-NTOU problem respect with the value of the TOU program variable considering different models for the responsive customers behavior.

is presented in Eq. (7). This constraint is applicable for the problem with/without implementation of the NDR program. Herein, implementing or not implementing the NDR program are indicated by variable$y^{\delta}(.)$. In other words, the generation and demand of the system with/without implementation of NDR programs must be equal.

$$\sum_{g\in S_g} P_g(t)\times y_g^{CS}(t) = \sum_{\phi\epsilon S_\phi}\sum_{\xi\epsilon S_\xi}(D^0_{\phi,\xi}(t) \times(1-y^{\delta}(t)) + D^{\delta}_{\phi,\xi}(t)\times y^{\delta}(t)), \qquad \forall t\in S_t, \forall \delta\in S_\delta \tag{7}$$

2.3.2. System minimum generation constraint

The constraint of minimum power of the system generated by "on" units for every hour of the operation period is presented in Eq. (8). In other words, the units, which are "on", must be able to supply the minimum demand level of the system.

$$\sum_{g\in S_g} P_g^{min}\times y_g^{CS}(t) \le \sum_{\phi\epsilon S_\phi}\sum_{\xi\epsilon S_\xi}(D^0_{\phi,\xi}(t) \times(1-y^{\delta}(t)) + D^{\delta}_{\phi,\xi}(t)\times y^{\delta}(t)), \forall t\in S_t \tag{8}$$

2.3.3. System maximum generation constraint considering spinning reserve

The maximum generation of the power system considering spinning reserve level provided by "on" units for every hour of the operation period is presented in Eq. (9). In other words, the units, which are "on", must be able to supply the maximum demand level of the system considering the required spinning reserve of the system.

$$\sum_{g\in S_g} P_g^{max}\times y_g^{CS}(t) \ge \sum_{\phi\epsilon S_\phi}\sum_{\xi\epsilon S_\xi}(D^0_{\phi,\xi}(t) \times(1-y^{\delta}(t)) + D^{\delta}_{\phi,\xi}(t)\times y^{\delta}(t)) + SR(t), \forall t\in S_t \tag{9}$$

2.3.4. Units' power constraint

The maximum and minimum power constraints of every generation unit at every hour of the operation period is presented in Eq. (10). In other words, the generation unit cannot generate power beyond the upper and lower limits.

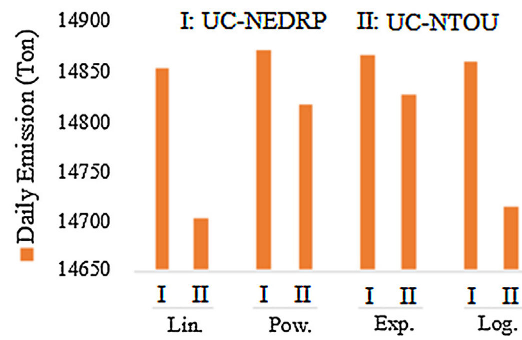

Fig. 5. Total greenhouse gas emissions (ton/day) released by the system in the optimal UC-NDR problems considering different models for the responsive customers behavior.

$$(P_g^{min} \le P_g(t) \le P_g^{max})\times y_g^{CS}(t), \quad \forall t\in S_t, \forall g\in S_g \tag{10}$$

2.3.5. Units' ramp-up rate and ramp-down rate constraints

The ramp-up rate and ramp-down rate constraints of every generation unit at every hour of the operation period are presented in Eqs. (11) and (12), respectively. In other words, the generation unit is able to increase and decrease its generation level with the definite rates.

$$((P_g(t+1)-P_g(t)) \le RUR_g)\times y_g^{CS}(t), \quad \forall t\in S_t, \quad \forall g\in S_g \tag{11}$$

$$((P_g(t)-P_g(t+1)) \le RDR_g)\times y_g^{CS}(t), \quad \forall t\in S_t, \quad \forall g\in S_g \tag{12}$$

2.3.6. Units' minimum "off time" and minimum "on time" constraints

The minimum "off time" and minimum "on time" constraints of every generation unit at every hour of the operation period are presented in Eqs. (13) and (14), respectively. In other words, the generation unit cannot be turned on sooner than the minimum off time interval after it has been turned off. Also, the generation unit cannot be turned off sooner than the minimum on time duration after it has been turned on.

$$\mathrm{OFFT}_g(t) \ge \mathrm{MDT}_g, \quad \forall t\in S_t, \quad \forall g\in S_g \tag{13}$$

$$\mathrm{ONT}_g(t) \ge \mathrm{MUT}_g, \quad \forall t\in S_t, \quad \forall g\in S_g \tag{14}$$

3. Demand and cost models of nonlinear demand response programs

Detailed definition and description of DR programs have been presented in Refs. [20–22]. In the following, the modelings of nonlinear EDRP and TOU program proportional to various nonlinear behavior of responsive customers behavior respect with different policies of the NDR program designer are presented. Investigation NDR programs (in addition to linear DR programs) for nonlinear behavioral models of the responsive customers (in addition to linear behavioral model of the responsive customers) is necessary, since, in the real world, the responsive customers do not have unique and linear reaction to the schemes of the DR programs. Herein, the nonlinear models include power model, exponential model, logarithmic model, and linear model as the particular state of the nonlinear model. These modelings are based on price elasticity of demand and consumers' surplus function [19]. In addition to the above mentioned modelings, the implementation cost models of nonlinear EDRP and TOU are formulated and presented.

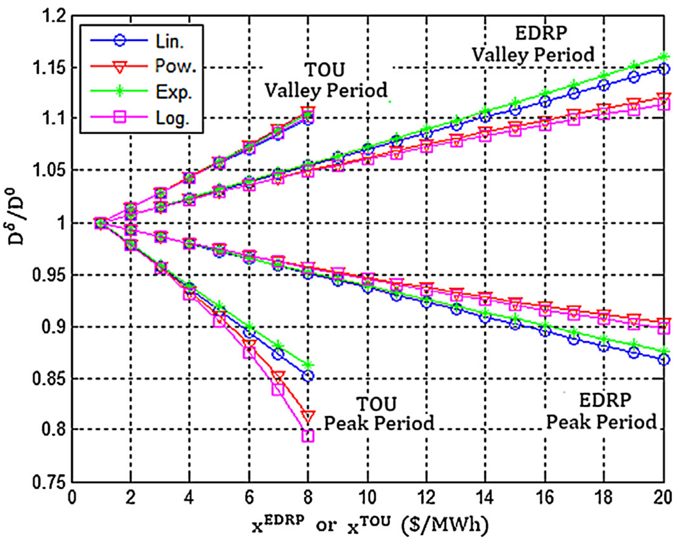

Fig. 6. Sensitivity analysis for ratio of revised demand to initial demand respect with the value of variable of NDR program for valley and peak periods considering different models for the responsive customers behavior.

Table 1
Hourly demand of the residential customers' classes with different behavioral models (MW).

Hour	Class 1 (linear)	Class 2 (power)	Class 3 (exponential)	Class 4 (logarithmic)
1	173	85	261	181
2	181	85	261	181
3	165	101	261	165
4	149	85	277	181
5	157	117	261	165
6	101	133	261	181
7	109	149	277	165
8	50	195	315	160
9	55	205	485	165
10	55	205	515	205
11	55	205	545	215
12	55	215	525	215
13	55	225	515	225
14	125	235	485	215
15	185	245	475	215
16	250	255	425	195
17	275	255	385	165
18	375	465	330	83
19	452	591	285	83
20	474	618	294	78
21	515	600	285	74
22	497	600	285	65
23	399	528	294	69
24	359	501	267	69

Table 2
Self and cross price elasticity of demand at different periods.

Period	Valley (t:1–8)	Off-peak (t:9–17)	Peak (t:18–24)
Valley	−0.145	0.008	0.223
Off-peak	0.013	−0.090	0.035
Peak	0.105	0.004	−0.200

3.1. Demand model of nonlinear demand response programs

3.1.1. Demand model of nonlinear emergency demand response program

Demand model after implementation of NDR programs considering different nonlinear models for responsive customer behavior have been presented in Ref. [19]. Since in EDRP energy price is the same in different periods (valley, off-peak, and peak), the presented demand models can be revised for implementation of nonlinear EDRP as follows. As can be seen in Eqs. (15)–(18), the only motivation for changing the demand pattern by the responsive customer is value of the introduced incentive (I^{EDRP}). In other words, if the value of incentive is zero, the demand pattern will be the same as initial demand pattern.

3.1.1.1. Power model.

$$D^{EDRP}_{\phi,Pow}(t) = D^{0}_{\phi,Pow}(t) \times \prod_{t' \in S_t} \left(\frac{I^{EDRP}(t') + \pi^{0}(t')}{\pi^{0}(t')}\right)^{E_{\phi}(t,t')},$$
$$S_t = \{1, \ldots, Nt\} \tag{15}$$

3.1.1.2. Exponential model.

$$D^{EDRP}_{\phi,Exp}(t) = D^{0}_{\phi,Exp}(t) \times e^{\left(\sum_{t' \in S_t} \frac{I^{EDRP}(t')}{\pi^{0}(t')} \times E_{\phi}(t,t')\right)} \tag{16}$$

3.1.1.3. Logarithmic model.

$$D^{EDRP}_{\phi,Log}(t) = D^{0}_{\phi,Log}(t) \times \left(1 + \sum_{t' \in S_t} \left(\ln\frac{I^{EDRP}(t') + \pi^{0}(t')}{\pi^{0}(t')}\right) \times E_{\phi}(t,t')\right) \tag{17}$$

3.1.1.4. Linear model.

$$D^{EDRP}_{\phi,Lin}(t) = D^{0}_{\phi,Lin}(t) \times \left(1 + \sum_{t' \in S_t} \frac{I^{EDRP}(t')}{\pi^{0}(t')} \times E_{\phi}(t,t')\right) \tag{18}$$

where

$$I^{EDRP}(t) = \begin{cases} 0 & t \notin PeakPeriod \\ x^{EDRP} & t \in PeakPeriod \end{cases} \tag{19}$$

3.1.2. Demand model of nonlinear time of use program

Since there is no incentive in TOU program, the presented demand model for implementation of NDR programs [19] can be revised for nonlinear TOU program, as follows. As can be seen in Eqs. (20)–(23), the only motivation for modifying the demand pattern by the responsive customer is the existence of difference between the electricity prices at different periods. In other words, if the value of the electricity price is constant throughout the day, the responsive customer will not change its demand pattern.

3.1.2.1. Power model.

$$D^{TOU}_{\phi,Pow}(t) = D^{0}_{\phi,Pow}(t) \times \prod_{t' \in S_t} \left(\frac{\pi^{TOU}(t')}{\pi^{0}(t')}\right)^{E_{\phi}(t,t')} \tag{20}$$

3.1.2.2. Exponential model.

$$D^{TOU}_{\phi,Exp}(t) = D^{0}_{\phi,Exp}(t) \times e^{\left(\sum_{t' \in S_t} \frac{\pi^{TOU}(t') - \pi^{0}(t')}{\pi^{0}(t')} \times E_{\phi}(t,t')\right)} \tag{21}$$

3.1.2.3. Logarithmic model.

$$D^{TOU}_{\phi,Log}(t) = D^{0}_{\phi,Log}(t) \times \left(1 + \sum_{t' \in S_t} \left(\ln\frac{\pi^{TOU}(t')}{\pi^{0}(t')}\right) \times E_{\phi}(t,t')\right) \tag{22}$$

3.1.2.4. Linear model.

$$D^{TOU}_{\phi,Lin}(t) = D^{0}_{\phi,Lin}(t) \times \left(1 + \sum_{t' \in S_t} \frac{\pi^{TOU}(t') - \pi^{0}(t')}{\pi^{0}(t')} \times E_{\phi}(t,t')\right) \tag{23}$$

Table 3
Results of the UC and UC-NDR problems.

	UC	Optimal UC-NEDRP	Optimal UC-NTOU
Optimal NDR program variable ($/MWh)	0	7	12
Total cost ($/day)	672,190	665,150	643,620
Total greenhouse gas emissions (ton/day)	14,934	14,867	14,774
Cost saving ($/year)	–	2,569,400	10,427,000
Greenhouse gas emissions reduction (ton/year)	–	24,484	58,550

where

$$\pi^{TOU}(t) = \begin{cases} \pi^0(t) - x^{TOU} & t \in ValleyPeriod \\ \pi^0(t) & t \in Off-PeakPeriod \\ \pi^0(t) + x^{TOU} & t \in PeakPeriod \end{cases} \quad (24)$$

In fact, the electrical energy price is adjusted at valley and peak periods using x^{TOU} as the price regulator of TOU program.

3.2. Cost model of nonlinear demand response programs

Implementing NDR program has some cost or benefit for NDR program providers, as they pay incentive to the residential customers for demand reduction at peak period (based on the voluntary IBPs), penalizes them for their violation (based on the mandatory IBPs), or it is because of price and demand changes (based on the TBR programs). EDRP is a voluntary IBPs, thus the implementation cost of the EDRP can be formulated as Eq. (25) that includes the value of incentive paid to the residential customers for their demand reduction at peak period. Also, implementation cost of TOU program as a TBR program can be written as Eq. (26). Implementing TOU program may result in profit for NDR program provider when the income of sold energy is increased after implementation of this program. In this condition, the cost value is negative.

$$C^{EDRP}_{\phi,\xi}(t) = I^{EDRP}(t) \times (D^0_{\phi,\xi}(t) - D^{EDRP}_{\phi,\xi}(t)) \quad (25)$$

$$C^{TOU}_{\phi,\xi}(t) = \pi^0(t) \times D^0_{\phi,\xi}(t) - \pi^{TOU}(t) \times D^{TOU}_{\phi,\xi}(t) \quad (26)$$

3.2.1. Cost model of nonlinear emergency demand response program

By substituting Eqs. (15), (16), (17), and (18) in Eq. (25) and arranging it, the implementation cost of nonlinear EDRP for nonlinear behavioral models of responsive customer are obtained as follows. As can be seen in Eqs. (27)–(30), if there is no incentive, the implementation cost of the nonlinear EDRP will be zero.

3.2.1.1. Power model.

$$C^{EDRP}_{\phi,Pow}(t) = I_{EDRP}(t) \times D^0_{\phi,Pow}(t) \times \left(1 - \prod_{t' \in S_t} \left(\frac{I^{EDRP}(t') + \pi^0(t')}{\pi^0(t')}\right)^{E_\phi(t,t')}\right) \quad (27)$$

3.2.1.2. Exponential model.

$$C^{EDRP}_{\phi,Exp}(t) = I^{EDRP}(t) \times D^0_{\phi,Exp}(t) \times \left(1 - e^{\left(\sum_{t' \in S_t} \frac{I^{EDRP}(t')}{\pi^0(t')} \times E_\phi(t,t')\right)}\right) \quad (28)$$

3.2.1.3. Logarithmic model.

$$C^{EDRP}_{\phi,Log}(t) = -I_{EDRP}(t) \times D^0_{\phi,Log}(t) \times \sum_{t' \in S_t} \left(ln \frac{I^{EDRP}(t') + \pi^0(t')}{\pi^0(t')}\right) \times E_\phi(t,t') \quad (29)$$

3.2.1.4. Linear model.

$$C^{EDRP}_{\phi,Lin}(t) = -I^{EDRP}(t) \times D^0_{\phi,Lin}(t) \times \sum_{t' \in S_t} \frac{I^{EDRP}(t')}{\pi^0(t')} \times E_\phi(t,t') \quad (30)$$

3.2.2. Cost model of nonlinear time of use program

By substituting Eqs. (20), (21), (22), and (23) in Eq. (26), the implementation cost of nonlinear TOU program for nonlinear behavioral models of responsive customers are achieved as follows. As can be seen in Eqs. (31)–(34), if the value of electricity price is not changed, there will be no benefit or cost for the implementation of the nonlinear TOU program.

3.2.2.1. Power model.

$$C^{TOU}_{\phi,Pow}(t) = D^0_{\phi,Pow}(t) \times \left(\pi^0(t) - \pi^{TOU}(t) \times \prod_{t' \in S_t} \left(\frac{\pi^{TOU}(t')}{\pi^0(t')}\right)^{E_\phi(t,t')}\right) \quad (31)$$

3.2.2.2. Exponential model.

$$C^{TOU}_{\phi,Exp}(t) = D^0_{\phi,Exp}(t) \times \left(\pi^0(t) - \pi^{TOU}(t) \times e^{\left(\sum_{t' \in S_t} \frac{\pi^{TOU}(t') - \pi^0(t')}{\pi^0(t')} \times E_\phi(t,t')\right)}\right) \quad (32)$$

3.2.2.3. Logarithmic model.

$$C^{TOU}_{\phi,Log}(t) = D^0_{\phi,Log}(t) \times (\pi^0(t) - \pi^{TOU}(t) \times \left(1 + \sum_{t' \in S_t} \left(ln \frac{\pi^{TOU}(t')}{\pi^0(t')}\right) \times E_\phi(t,t')\right)) \quad (33)$$

3.2.2.4. Linear model.

$$C^{TOU}_{\phi,Lin}(t) = D^0_{\phi,Lin}(t) \times (\pi^0(t) - \pi^{TOU}(t) \times \left(1 + \sum_{t' \in S_t} \frac{\pi^{TOU}(t') - \pi^0(t')}{\pi^0(t')} \times E_\phi(t,t')\right)) \quad (34)$$

4. The proposed optimization technique for the UC-NDR problem

In this study, simulated annealing (SA) algorithm is applied to solve the optimization problem. Other optimization algorithms could be used in this problem; however, simplicity of SA algorithm along with its powerful search ability in complex and nonlinear environments are the advantages compared to other algorithms [23]. Herein, the value of the objective function (the total cost of UC-NDR problem over the operation period) is defined as the value of internal energy of molten metal (ε) and then it is tried to minimize this energy. This process is performed for both nonlinear EDRP and TOU and for all the possible values of their variables (x^{EDRP}, x^{TOU}). Then, the optimal type of the NDR program and the optimal value

Table 4
Generation scheduling and spinning reserve in the optimal scheme of the UC-NEDRP problem (MW).

t	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	SR
1	455	150	31	76	25	0	0	0	0	0	595
2	455	150	35	80	25	0	0	0	0	0	578
3	455	150	26	72	25	0	0	0	0	0	604
4	455	150	26	72	25	0	0	0	0	0	604
5	455	150	31	76	25	0	0	0	0	0	595
6	455	150	20	61	25	0	0	0	0	0	621
7	455	150	30	76	25	0	0	0	0	0	596
8	455	150	41	86	25	0	0	0	0	0	575
9	455	177	130	130	25	0	0	0	0	0	415
10	455	248	130	130	25	0	0	0	0	0	344
11	455	288	130	130	25	0	0	0	0	0	304
12	455	278	130	130	25	0	0	0	0	0	314
13	455	288	130	130	25	0	0	0	0	0	304
14	455	328	130	130	25	0	0	0	0	0	264
15	455	389	130	130	25	0	0	0	0	0	203
16	455	394	130	130	25	0	0	0	0	0	198
17	455	349	130	130	25	0	0	0	0	0	243
18	455	455	130	130	25	0	0	0	0	0	137
19	455	455	130	130	131	20	25	0	0	0	151
20	455	455	130	130	162	29	25	0	0	10	156
21	455	455	130	130	162	39	25	0	0	10	146
22	455	455	130	130	155	20	25	0	0	10	172
23	455	455	130	130	40	20	0	0	0	0	182
24	455	401	130	130	25	0	0	0	0	0	191

for its variable are discovered based on the minimum total cost of the UC-NDR problem. In every SA algorithm, demand profile of the customers are determined based on their behavioral model and introducing the scheme of NDR program by considering incentive for demand reduction at peak period by using x^{EDRP} (the concept of EDRP) and changing the price of the electricity by applying x^{TOU} (the concept of the TOU program). In the following, different steps for applying SA algorithm in the UC-NDR problem are presented and described.

- *Step 1: primary data*

Parameters for applying SA: these parameters includes initial temperature of molten metal (θ_0), number of generating new random state at every temperature (N^{SA}), and value of coefficient for gradually decreasing temperature of the molten metal (μ).

Parameters of the system: values of all the system parameters and the initial data including generation units' parameters and hourly demand levels of the residential customers with any class are obtained.

Variable of the NDR program: value of the variable (x^{EDRP}orx^{TOU}) and type of the selected NDR program (nonlinear EDRP or TOU) are determined.

Implementing the NDR program: the selected NDR program with its defined variable is implemented for every residential customer's class considering its nonlinear behavioral model, and then the revised demand of the system is determined by summing the updated demand of the residential customers with any class.

Initial solution: a random solution for the problem variables is generated as an initial solution that includes the binary values for commitment status of the generation units for all hours of the operation period (one day).

- *Step 2: generating an acceptable solution*

Generating new solution: a random solution for the problem variables is generated in the vicinity of the old one.

Running economic dispatch: herein, Lambda-iteration method is used to run the economic dispatch problem.

Checking problem constraints: all the problem constraints are checked and if they are correct, value of the internal energy of molten metal is measured and the algorithm goes on; otherwise, the process is repeated form Step 2.

Checking SA acceptance criterion: the SA acceptance criterion is presented in Eq. (35). Based on this principle, the problem solution resulted in decreased internal energy of molten metal is always accepted; however, the solution with the increased value of the internal energy is accepted just by an adaptive probability presented in Eq. (36). The value of this adaptive probability is decreased as the molten metal is cooled.

$$y_k^{SA}\begin{cases} 1 & if \varepsilon_{k+1} < \varepsilon_k \\ 1 & if \varepsilon_{k+1} \geq \varepsilon_k, r_k > p_k \\ 0 & if \varepsilon_{k+1} \geq \varepsilon_k, r_k \leq p_k \end{cases} \quad (35)$$

$$p_k = e^{-\frac{\varepsilon_{k+1}-\varepsilon_k}{\theta_k}} \quad (36)$$

- *Step 3: checking the number of iteration for the current temperature*

If the number of iteration in the current temperature is not equal to the predefined value (N^{SA}), the process is repeated form Step 2; otherwise, temperature of the molten metal is decreased based on Eq. (37).

$$\theta_{k+1} = \mu \times \theta_k \quad (37)$$

Table 5
Generation scheduling and spinning reserve in the optimal scheme of the UC-NTOU problem (MW).

t	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	SR
1	455	150	77	121	25	0	0	0	0	0	504
2	455	150	82	126	25	0	0	0	0	0	494
3	455	150	73	116	25	0	0	0	0	0	513
4	455	150	73	116	25	0	0	0	0	0	513
5	455	150	78	121	25	0	0	0	0	0	503
6	455	150	64	108	25	0	0	0	0	0	530
7	455	150	79	122	25	0	0	0	0	0	501
8	455	150	96	130	25	0	0	0	0	0	476
9	455	175	130	130	25	0	0	0	0	0	417
10	455	245	130	130	25	0	0	0	0	0	374
11	455	285	130	130	25	0	0	0	0	0	307
12	455	275	130	130	25	0	0	0	0	0	317
13	455	285	130	130	25	0	0	0	0	0	307
14	455	326	130	130	25	0	0	0	0	0	266
15	455	386	130	130	25	0	0	0	0	0	206
16	455	391	130	130	25	0	0	0	0	0	201
17	455	346	130	130	25	0	0	0	0	0	246
18	455	341	130	130	25	0	0	0	0	0	251
19	455	455	130	130	27	20	0	0	0	0	195
20	455	455	130	130	72	20	0	0	0	0	150
21	455	455	130	130	81	20	0	0	0	0	141
22	455	455	130	130	58	20	0	0	0	0	164
23	455	373	130	130	25	0	0	0	0	0	219
24	455	291	130	130	25	0	0	0	0	0	171

- *Step 4: Concluding*

Checking temperature of the molten metal: temperature of the molten metal is measured and if the molten metal is frozen, the optimization process is finished; otherwise, the process is repeated form Step 2.

Introducing outcomes: the consequences include the optimal values for the total cost of the UC-NDR problem, generation level of the units, greenhouse gas emissions level of the system, and demand level of the residential customers with any class.

5. Numerical study

5.1. Primary data and the characteristics of the power system under study

The data of the power system including the fuel cost coefficient of the generation units, power limits of the units, minimum up/down time of the units, initial status of the units, and start-up cost of the units have been presented in Ref. [24]. In this study, in addition to the above mentioned data, ramp up rate, ramp down rate, and shut down cost of the generation units are taken into consideration in the problem. The value of the ramp up/down rates of units 1–5 and units 6–10 are assumed to be about 120 MW/h and 50 MW/h, respectively. Also, shut down cost and start-up cost of the generation units are assumed about hot start-up cost presented in Ref. [24]. Moreover, the minimum value of spinning reserve at every hour of a day is assumed about 10% of demand at the same hour. Herein, the generation units are considered to be steam-electric generator [25]. Also, the type of the fuel consumed by the units 1–7 and unit 10 is considered to be Natural Gas and types of the fuels consumed by the unit 8 and unit 9 are considered Sub-bituminous and Residual Oil (No. 6), respectively [25]. The number of pounds of greenhouse gas emissions released by a typical steam-electric generator for different types of the fuel have been presented in Ref. [25]. Furthermore, the value of penalty for greenhouse gas emissions is assumed about $10 per ton based on the California Air Resources Board auction of greenhouse gas emissions [26]. Additionally, Table 1 presents the hourly demand levels of the residential customers' classes 1–4 with behavioral models of linear, power, exponential, and logarithmic, respectively. The given customers' classes have different hourly demand profile and different reaction to the schemes of NDR programs based on the given functions in Eqs. (15)–(18) and Eqs. (20)–(23) for implementation of nonlinear EDRP and nonlinear TOU program, respectively.

The self and cross price elasticity of demand of residential customers at different periods including valley, off-peak, and peak periods presented in Ref. [19] are given in Table 2 after some revisions.

Herein, the electricity price at every period is considered to be about the average value of the hourly marginal cost prices at the same period. Based on this, the electricity prices in the UC problem are determined about $22.77/MWh, $23.54/MWh, and $28.61/MWh for valley, off-peak, and peak periods, respectively.

In the following, at first, the UC-NDR problem is simulated on the given power system assuming the behavioral models of the residential customers' classes and the results are compared with the outcomes of the UC problem (without NDR). Then, various analyses are performed to investigate the effects of different NDR programs on the commitment status of the generation units, the system operation cost, greenhouse gas emissions level of the units, and the system demand level. Herein, in all the simulations, value of the SA algorithm parameters including θ_0, N^{SA}, and μ are considered about 900 centigrade, 90 times, and 0.9, respectively.

Table 6
Differences in commitment status of the units in the UC-NEDRP and UC-NTOU compared to UC.

Model	Problem	Unit	Hour: 1-24
Lin., Pow., Exp., Log.	UC-NEDRP	U6	000000000000000000111110
		U7	000000000000000000111100
		U8	000000000000000000000000
		U9	000000000000000000000000
		U10	000000000000000000011100
Lin.	UC-NTOU	U6	000000000000000000011100
		U7	000000000000000000000000
		U8	000000000000000000000000
		U9	000000000000000000000000
		U10	000000000000000000000000
Pow.	UC-NTOU	U6	000000000000000000111000
		U7	000000000000000000011100
		U8	000000000000000000000000
		U9	000000000000000000000000
		U10	000000000000000000000000
Exp., Log.	UC-NTOU	U6	000000000000000000111100
		U7	000000000000000000000000
		U8	000000000000000000000000
		U9	000000000000000000000000
		U10	000000000000000000000000

Table 7
Optimal variables of the NDR programs and minimum total cost in the UC-NDR considering different models for the responsive customers behavior.

Responsive customer behavioral model	Problem	Optimal NDRP variable ($/MWh)	Minimum total cost ($/day)
Lin.	UC-NEDRP	7	664,810
	UC-NTOU	12	642,840
Pow.	UC-NEDRP	7	665,240
	UC-NTOU	10	644,650
Exp.	UC-NEDRP	7	665,230
	UC-NTOU	12	642,570
Log.	UC-NEDRP	7	664,880
	UC-NTOU	11	643,760

5.2. Investigating optimal scheme of UC-NDR

Table 3 presents results of the UC, UC-NEDRP and UC-NTOU problems. As can be seen, the value of total cost and greenhouse gas emissions level of the system over the operation period (one day) in the UC problem are about $672,190 and 14,934 tons/day, respectively. After running the UC-NDR problem, the value of NDR program variable in the UC-NEDRP and UC-NTOU problems are obtained about $7/MWh as the incentive of EDRP and $12/MWh as the price regulator of TOU, respectively. Moreover, the total cost of the UC-NEDRP and UC-NTOU problems are achieved about $665,150/day and $643,620/day, respectively. Therefore, the best strategy for implementation of NDR program in the UC problem is TOU with price regulator of $12/MWh. In other words, the optimal scheme for electricity prices are about $34.77/MWh, $23.54/MWh, and $16.61/MWh for valley, off-peak and peak periods, respectively. In addition, as can be seen in Table 3, by running the optimal UC-NEDRP and UC-NTOU rather than UC, the value of yearly saving ($) and yearly greenhouse gas emissions reduction (ton) are notable.

The reason for the reduction of the total cost and greenhouse gas emissions of the system is leveling the demand profile of the system by implementation of the NDR programs, since the fuel cost and greenhouse gas emissions of the thermal power plants are quadratic polynomial functions (as can be seen in Eqs. (2) and (3)). This phenomenon can be observed in Fig. 2 because the demand profile of the customers with any class have become more flat after the implementation of the NDR programs. In other words, a more flat demand profile will have less fuel consumption and less greenhouse gas emissions for the thermal power plants (with the same amount of demand over the operation period (one day)).

Fig. 2 demonstrates the initial demand of the residential customers' classes 1–4 and their demand level after implementation of the best scheme of UC-NTOU (price regulator of $12/MWh or $34.77/MWh, $23.54/MWh, and $16.61/MWh for valley, off-peak and peak periods, respectively). As can be seen, every residential customers' class with any behavioral model has shifted some of its demand from the peak period to off-peak and valley periods.

Table 4 presents generation scheduling and spinning reserve level of the system for the optimal scheme of the UC-NEDRP problem ($7/MWh as the incentive). The highlighted values indicate the differences in the generation level of the units between UC-NEDRP and UC problems. Moreover, the red squares demonstrate differences in the commitment status of the units between the above mention problems. As can be seen, generation scheduling of the units 2–10 have been revised and commitment status of units 6–10, as the most pollutant and the most expensive units, have been changed in the scheduling period. In other words, commitment of the units 6–7 and the unit 10 have been differed, and the units 8–9 have been kept off in the whole scheduling period in the optimal UC-NEDRP.

In addition, generation scheduling and spinning reserve level of the system for the optimal UC-NTOU ($12/MWh as the price regulator) are given in Table 5. The highlighted quantities and red squares point to the differences in the generation level and commitment status of the units between UC-NTOU and UC problems, respectively. As can be seen, generation scheduling of the units 2–5 have been modified, commitment of the unit 6 have been decreased and the units 7–10 have been kept off in the whole scheduling period.

5.3. Sensitivity analyses

Herein, in all the sensitivity analyses, the behavioral models of the residential customers' classes in Table 1 are not considered for the sensitivity analyses purposes and their behavioral models are assumed to be the same and defined based on the performed analysis.

5.3.1. Sensitivity analysis for the commitment status of units

Table 6 presents commitment status of the generation units in the UC-NEDRP and UC-NTOU problems and their dissimilarities with the UC problem. As can be seen, commitment status of the units in the UC-NTOU considering different responsive customers behavioral models are not identical and compatible. Therefore, these inconsistences indicate that unreal modeling of the responsive customers behavioral model can affect the commitment status of the units.

5.3.2. Sensitivity analysis for the total cost of the problem

The sensitivity curves concerned with the total cost of the UC-NEDRP and UC-NTOU problems respect with their NDR program variable have been illustrated in Figs. 3 and 4, respectively. As can be seen, the presented curves have nonlinear behavior respect with increasing value of their NDR program variable and there is just one optimal point for every curve. The optimal values for incentive of the nonlinear EDRP and price regulator of the nonlinear TOU, and also minimum total cost of the NEDRP and UC-NTOU problems have been presented in Table 7. As can be seen, the achieved values are not identical. Thus, it can be concluded that responsive customers behavioral must be modeled correctly, since this issue can affect the consequences of the problem and lead to misleading result for the total cost of the problem.

The amount of daily greenhouse gas emissions of the generation units in the optimal UC-NEDRP and UC-NTOU problems considering different models for the responsive customers behavior are demonstrated in Fig. 5. As can be seen, the greenhouse gas emissions level of the system for various models are not the same and this result indicates the necessity for appropriate modeling of the responsive customers behavior.

5.3.3. Sensitivity analysis for demand level

Fig. 6 demonstrates the ratio of demand after implementation of nonlinear EDRP to initial demand respect with value of the EDRP variable (incentive) for valley and peak periods considering different nonlinear models for the responsive customers behavior. Also, the same sensitivity analysis has been presented for the TOU program respect with variable of TOU (price regulator) in Fig. 6. As can be seen, by increasing the value of variables, the demand ratios are decreased in peak period and they are increased at valley period with nonlinear trends. In other words, the responsive customers with different behavioral models do not react identically respect with the value of variables of EDRP and TOU program. Therefore, it can be concluded that unrealistic modeling of the responsive customer behavior may result in unpredicted demand level.

6. Conclusion

The investigated study demonstrated that cooperation of the responsive residential customers in the UC problem is advantageous and can decrease the total cost of the problem and the greenhouse gas emissions level of the thermal power plants. In addition, it was shown that determining the optimal scheme of the NDR program in the UC-NDR problem is necessary. Moreover, sensitivity analyses indicated that how the consequences of the UC-NDR problem can be affected by the different responsive customers behavioral models and the policies introduced by the NDR program designer. Therefore, comprehensive studies and modelings are needed to realistically characterize the responsive customers behavioral model.

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